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DEPARTMENT OF ECONOMICS

Essays in Development Economics

Ada Isabel González-Torres Fernández

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

Florence, 12 October 2018

European University Institute
Department of Economics

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I, Ada Isabel Gonzalez-Torres Fernandez, certify that I am the author of the work "Essays in Development Economics" I have presented for examination for the PhD thesis at the European University Institute. I also certify that this is solely my own original work, other than where I have clearly indicated, in this declaration and in the thesis, that it is the work of others.

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Statement of inclusion of previous work (if applicable):

I confirm that chapter 2 was jointly co-authored with Elena Esposito and that I contributed at least 50% of the work.

Signature and Date: Ada Isabel Gonzalez-Torres Fernandez, October 3, 2018

A mi familia.

To West Africans, may their bravery inspire all.

To women, to those who succeeded, and to those who were forgotten.

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Abstract

This dissertation studies the nexus between weak institutions, epidemic disease and conflict.

In the first chapter I provide descriptive evidence of an empirical pattern found across countries that introduces the two main chapters of the dissertation. Countries with higher incidence of disease outbreaks are more likely to exhibit civil violence, conditional on population and income. This effect varies, however, with institutions and health expenditure. The relationship disappears in countries with above average political rights or above average civil liberties. There is some evidence that health investments last year also diminish the relationship between disease outbreaks this year and civil violence next year. This descriptive evidence suggests that while disease outbreaks are associated with social unrest, this depends on the particular institutions at hand and there is scope for public policy interventions that halt both the burden of disease and civil conflict.

The second chapter, co-authored with Elena Esposito, seeks to identify the causal impact of a rapidly spreading epidemic on civil violence in the context of the largest Ebola outbreak in history, in Western Africa. The identification strategy relies on the epidemiological features of the Ebola Virus Disease (EVD). We exploit the dynamics of the disease and weekly frequency data at the local level to analyze the effect of new infections on riots, protests and violence against institutional authorities. The impacts are large, localized and tied to containment efforts. The results suggest that state coercion and demand for public goods are mechanisms fueling conflict. Containing the epidemic requires a change in cultural practices which leads to social unrest, especially for groups facing higher costs of cultural adaptation, low trust in institutional authorities and depending on the response of the state. This further deepens mistrust in institutions after the epidemic, especially among these communities.

In the third and last chapter I study the impact of local radios on the spread of a major epidemic in the context of the Ebola outbreak in Guinea in 2014-16. This is a unique setting to explore the role of media as a coordination device to change cultural norms in a high stakes environment. Using original data collected in Guinea and a quasi-experimental design based on exogenous variation in radio signal reception by distinct media outlets, combined with the precise timing of distinct information campaigns about Ebola, I seek to identify the effect of local radios on the spread of the disease, social resistance and treatment uptake. The results show that sustained access to a local radio program informing about protective measures, encouraging treatment, addressing Ebola rumors and new burial practices, lowered social resistance behavior, increased treatment uptake and led to a drop in infected cases seven months after the start of the campaign. Access to local radios affected cultural norms, such as burial practices, and facilitated technological adoption, but there is no evidence of impacts on private actions, such as chlorine use.

Contents

Chapter 1

Epidemic Disease and Conflict: Stylized facts

"Na ikaraka, como un grillo que se esconde en la noche: la verdad se oculta ante todos nosotros y solo tiendo a intuirla, a sentirla. Oigo su sonido lejano o cercano. Creo ser poseedor de ella, creo que es segura, creo que está allí, escondida, na ikaraka."

(Na ikaraka, like a cricket hiding in the night: the truth conceals itself from us all and I only tend to sense it, feel it. I hear its noise, near or far. I think I possess it, I think it is certain, I think it is there, hidden, na ikaraka.)

Edjanga Jones Ndjoli, *Heredarás la Tierra*

1.1 Introduction

The last decades have seen the emergence or re-emergence of infectious disease outbreaks throughout the world, with devastating consequences for developing countries, especially affecting the young, and causing worldwide alarm fearing contagion[1]. While the im-

[1] The 1918 influenza pandemic took the lives of 50 million people, HIV/AIDS killed over 35 million. While other epidemics, such as severe acute respiratory syndrome (SARS) in 2003, H1N1 in 2009 or the Ebola epidemic in 2014-15, had lower death tolls, they led to huge social and economic disruption (GHRF, 2016).

mediate effect of epidemics are clearly illness and death, their economic and political consequences are more complex and are at the center of the debate on why poor countries are poor (Bloom and Sachs, 1998; Acemoglu and Johnson, 2007). Developing countries are not only poorer and have weaker institutions than rich countries, they also have a higher risk of emerging infectious disease outbreaks and higher rates of civil violence[2]. Epidemics can lead to a poverty trap, as the social, economic and institutional disruption they carry can lead to social upheaval, especially in weak institutional settings, potentially further debilitating the state. On the other hand, depending on the nature of civil violence and the capacity of the state to respond to a disease outbreak, epidemics can also create an opportunity for technological and institutional change[3]. Understanding the drivers of civil violence and the state response to an epidemic is therefore critical to our understanding of economic development.

This chapter searches for empirical patterns that relate epidemics and civil violence throughout countries and diseases, and studies whether this relationship changes with institutions or health expenditure. The purpose is to provide descriptive evidence to study the generality of the findings of the main two chapters of the dissertation.

First we explore cross-country correlations between disease outbreaks and civil conflict, for Africa and a subset of countries in America and Asia, using data on disease outbreak alerts scraped from the World Health Organization (WHO) website and data on civil conflict constructed using the Armed Conflict Location and Event Data Project (ACLED)[4]. We then study whether this relationship varies for years and countries with better institutions

[2]Civil violence is perpetrated collectively by citizens or civilian organizations. Interpersonal and collective violence kills 12.3 people in 100'000 per capita in low income countries, compared to 2.6 people in 100'000 per capita being killed by interpersonal or collective violence in high income countries (WHO, 2015). On institutional determinants of poverty across countries vid. North (1990); Acemoglu et al. (2005, 2009); on evidence of emerging infectious disease outbreaks increasing mostly in the developing world vid. Jones et al. (2008).

[3]The Plague in 16th century Europe created an opportunity to develop better institutions, through its effect on raising the salience of public goods (Dittmar and Meisenzahl, 2016).

[4]ACLED Version 6 - 2016, for conflicts from 1997-2018 in Africa, South and South-East Asia. Additionally, Social Conflict Analysis Database (SCAD) are used for robustness. From 1990-2016 for Africa, Mexico, Central America and the Caribbean (Salehyan et al., 2012)

using the Freedom House Index on civil liberties and political rights and the Polity IV score on political regime characteristics and transitions (Marshall and Jaggers, 2002), or varying levels of yearly health expenditure at national level, using World Bank data. Secondly, in a panel estimation framework that relies on a Granger causality argument, we explore whether new disease outbreak alerts in a given year are predictive of greater conflict incidence in the next year, conditional on prior disease outbreaks, and whether this relationship changes with institutions or health expenditure.

The results show that countries with higher incidence of disease are more likely to exhibit civil violence, conditional on population and income. This effect varies, however, with institutions and health expenditure. The relationship disappears in countries with above average political rights or above average civil liberties. There is some evidence that greater health investments last year also diminish the relationship between disease outbreaks this year and civil violence next year. This descriptive evidence suggests that while disease outbreaks are associated with social unrest, this depends on the particular institutions at hand and there is scope for public policy interventions that halt both the burden of disease and civil conflict.

This chapter adds to the empirical literature on the determinants of conflict, thoroughly reviewed by Blattman and Miguel (2010). It is most related to recent evidence studying the impact of endemic diseases, pathogens and infectious diseases on conflict incidence. Cervellati et al. (2016) provide first evidence of vector-borne endemic diseases as drivers of civil conflict[5], using cross country variation in exposure to human pathogens. They suggest that the impact of endemic diseases on conflict incidence is a direct effect of health. Cervellati et al. (2017, 2018) investigate the effect of malaria on civil conflict in the African continent using data at sub-national grid-cells, studying long-term impacts, as well as effects at yearly frequency exploiting variation in climatic conditions favorable

[5] In some cases they are recurrently epidemic, such as malaria in some regions. Vector-borne diseases require vectors of transmission, which are living organisms that can transmit infectious diseases between humans or from animals to humans; for example mosquitoes.

for the transmission of malaria[6]. They suggest a health shock and a negative income shock as potential mechanisms and find exploratory evidence on the role of anti-malarial policies in lowering conflict incidence. This chapter seeks to contribute to this literature by showing that the impact of disease on conflict highly depends on the institutions at hand.

The next Section 1.2 describes the data. Section 1.3 provides descriptive evidence of the main correlates of civil violence. The event study is presented in Section 1.4. Section 1.5 concludes.

1.2 Data

The observations include 69 countries over 1997-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico. In some cases, due to data availability, we restrict the sample to 2004-2016 and exclude three outliers. The outcome of interest, civil conflict, is constructed using the Armed Conflict Location and Event Data Project (ACLED)[7]. Additionally, Social Conflict Analysis Database (SCAD) is used for robustness. The main explanatory variable, disease outbreak alerts, are scraped from the World Health Organization (WHO) website by the author. Three measures of institutions are used. The Freedom House Index provides an measure of civil liberties and political rights. Greater values of these scores indicate better institutions. Civil liberties include freedom of expression and belief, associational rights, rule of law and individual rights; political rights are an aggregate indicator of the electoral process, political pluralism and participation, and a functioning government; with higher values indicating more liberties or rights. Political transitions and regime characteristics (Marshall and Jaggers, 2002), are measured by the Polity IV index (version 2) from the Center for Systemic Peace. It captures this regime authority spectrum on a 21-point scale ranging from -10 (autocracy)

[6]They exploit the fact that the specific features of the malaria epidemiology imply temporary spikes in malaria transmission risk that are related to weather conditions and confined in time and space.

[7]ACLED Version 6 - 2016, for conflicts from 1997-2018 in Africa, South and South-East Asia. From 1990-2016 for Africa, Mexico, Central America and the Caribbean (Salehyan et al., 2012)

to +10 (consolidated democracy), with anocracies or mixed regimes[8] taking values -5 to +5 and other regimes taking value 0. Other covariates include population and GDP in 2010 constant US dollars (World Bank/OECD). Finally, health expenditure at national level is taken from WHO Global Health Expenditure data. This includes public health expenditure, defined as recurrent and capital spending from government budgets, external borrowings and grants (incl. donations from international agencies / NGOs), and social (or compulsory) health insurance funds; as well as private health expenditure, which includes direct household (out-of-pocket) spending, private insurance, charitable donations, and direct service payments by private corporations.

1.3 Correlates of Civil Conflict

This Section provides evidence of three correlates of conflict and in the next Section we study how they are interrelated. Firstly, we study the relationship between disease outbreak alerts and conflict incidence in Africa and a subset of countries in America and Asia. Secondly, we plot a well established relationship between weak institutions and conflict. Thirdly, we look at the correlation between health expenditure and conflict incidence.

We begin by showing descriptive statistics, Table 1.1. There is an average of 112 conflict events per year per country in the sample period 1997-2016, of which 35 are violent, 48 are riots and 2.5 describe an event that is explicitly health or disease-related, according to the description of the event[9]. Conflicts generate an average of 283 fatalities, 8 of which are due to riots in particular. In the sample period there are on average 0.5 new disease outbreak alerts per year for a given country.

Next we show a scatter plot of average yearly conflict and new disease outbreak alerts over

[8] An anocracy is loosely defined as a political system which is neither fully democratic nor fully autocratic, often being vulnerable to political instability.

[9] The description should include any of the words {Health, hospital, doctor, Ebola, malaria, disease, plague, cholera, AIDS, HIV, sick, illness}.

Table 1.1: Summary Statistics - Yearly Averages for all countries - 1997-2016

	All	All*	Africa	All** 2004/16
Conflicts: All	112.5	83.64	96.43	84.34
	(394.6)	(196.7)	(208.3)	(200.4)
Conflicts: Violent	35.19	29.36	33.85	29.20
	(101.9)	(74.65)	(79.21)	(75.54)
Conflicts: Riots	48.60	28.70	33.09	30.57
	(255.8)	(102.7)	(109.6)	(107.2)
Conflicts: Health/Disease-Motivated	2.493	1.310	1.510	1.374
	(14.87)	(4.152)	(4.424)	(4.307)
Conflicts in 100'000 per capita	4.200	4.119	4.749	4.032
	(10.73)	(10.72)	(11.39)	(10.63)
Fatalities due to Conflict	283.0	253.1	291.9	226.1
	(968.0)	(898.0)	(958.5)	(828.1)
Disease outbreak (excl. updates)	0.572	0.577	0.490	0.419
	(2.248)	(2.267)	(1.297)	(0.856)
Disease outbreak (incl. updates)	1.366	1.382	1.255	1.293
	(4.813)	(4.855)	(4.569)	(4.592)
Disease outbreak in 100'000 per capita (excl. updates)	0.0318	0.0324	0.0348	0.0282
	(0.131)	(0.132)	(0.140)	(0.126)
Civil Liberties	27.01	27.09	27.26	27.20
	(11.32)	(11.41)	(11.64)	(11.44)
Political Rights	16.11	16.13	16.22	16.17
	(10.11)	(10.18)	(10.02)	(10.24)
Polity IV	1.144	1.128	1.137	1.222
	(5.207)	(5.207)	(5.058)	(5.206)
Population in 100'000	492.0	469.9	212.7	476.2
	(1636.9)	(1644.3)	(281.5)	(1660.4)
GDP per capita in 2010 constant US dollars	4615.6	4623.4	4745.1	4702.8
	(5914.0)	(5969.5)	(6348.5)	(6069.7)
GDP in 2010 constant US dollars in 100'000 (PPP)	694214.8	675129.3	386391.6	697854.4
	(2160805.8)	(2176516.4)	(774305.3)	(2241425.7)
Public Health Expenditure (% of GDP)	2.528	2.560	2.704	2.600
	(1.387)	(1.380)	(1.399)	(1.405)
Private Health Expenditure (% of GDP)	3.023	3.041	3.056	3.065
	(1.628)	(1.638)	(1.716)	(1.666)
Observations	645	633	549	577

By Country per Year. * Excluding Pakistan and Somalia. ** Excluding Pakistan, Somalia, South Sudan.

Observations: 69 countries over 1997-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico. Data Sources: *Conflicts*: average number of yearly Conflicts (ACLED). Disease outbreak alerts (WHO). Population and GDP in 2010 constant US dollars (World Bank/OECD). *Public Health Expenditure*: recurrent and capital spending from government budgets, external borrowings and grants (incl. donations from international agencies / NGOs), and social (or compulsory) health insurance funds; *Private Health Expenditure* includes direct household (out-of-pocket) spending, private insurance, charitable donations, and direct service payments by private corporations (WHO Global Health Expenditure). *Civil Liberties*: civil liberties, aggregating freedom of expression and belief, associational rights, rule of law, individual rights; *Political Rights*: electoral process, political pluralism and participation, functioning government, with higher values indicating more liberties or rights (Freedom House Index). *Polity IV* (2): captures this regime authority spectrum on a 21-point scale ranging from -10 (autocracy) to +10 (consolidated democracy), (Center for Systemic Peace).

the sample period. Figure 1.1 shows a significant and positive correlation between disease outbreaks and conflict incidence, conditional on income per capita and population. This relationship could be due to conflict spreading new diseases or vice-versa, due to disease outbreaks fueling social unrest, a channel studied deeply in Chapter 2, or third factors influencing both. This is a stylized fact that holds also specifically for violent conflicts or disease-motivated conflict. The correlation is even larger when conditioning on civil liberties and political rights[10], but it becomes somewhat smaller when controlling for public and private health expenditure[11], suggesting that these are important variables underlying the relationship between epidemics and conflict incidence. The next Section 1.4 proposes an event study to explore the effect of institutions and health expenditure on the relationship between epidemics and conflict.

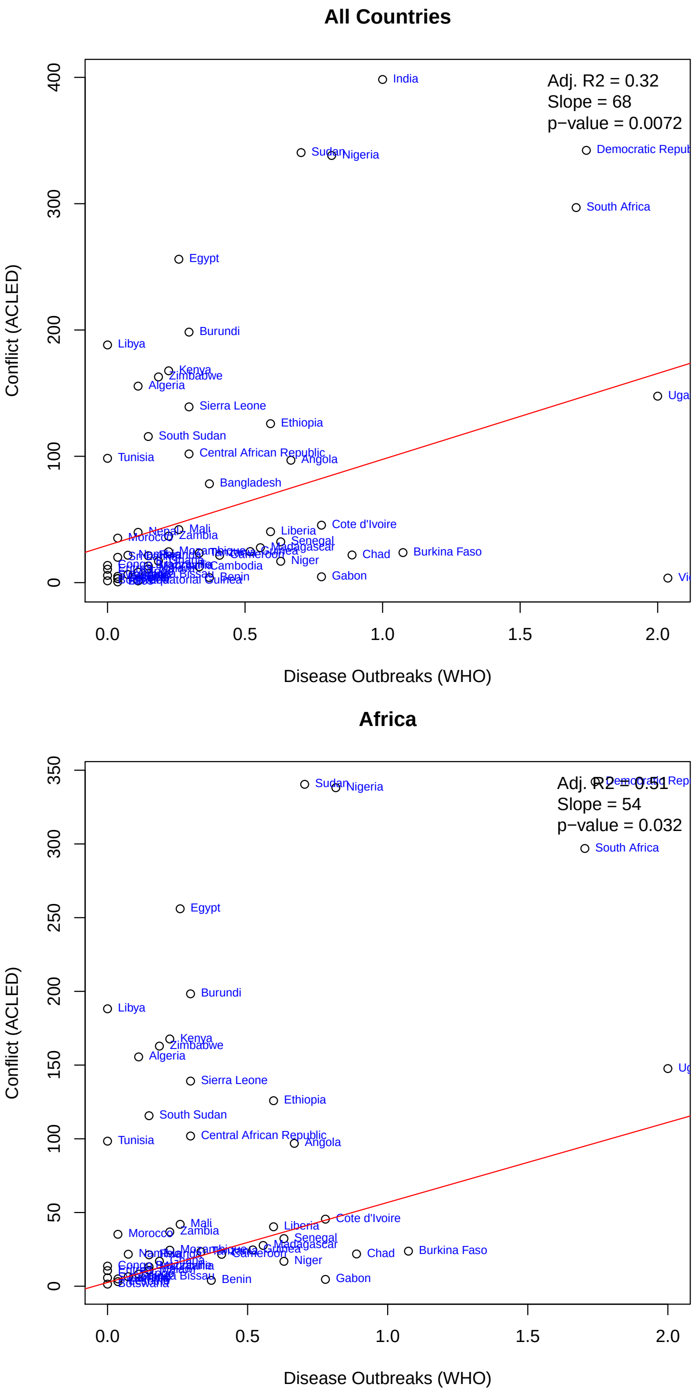
In this Chapter we study whether institutions affect the disease-conflict relationship. We begin by studying institutions in isolation. Figure 1.2 shows another stylized fact, namely that greater civil liberties are strongly associated with less likelihood of conflict. Civil liberties include freedom of expression and belief, associational and organizational rights, rule of law and individual rights. Political rights, which include the right to an electoral process, political pluralism and participation, and a functioning government, are also negatively related with conflict incidence, but the correlation is not significant overall, although it is within the African continent, Figure 1.3. This stylized fact is very intuitive, since better institutions can discourage the initiation of conflict, due to the threat of punishment, for instance, and also the opportunity cost of engaging in conflict is higher with better institutions. However, the threat of war can lead to greater political rights (Acemoglu and Robinson, 2005; Weinstein, 2005; Blattman and Miguel, 2010) and there is also evidence that the electoral processes can lead to social unrest in developing countries (Travaglianti, 2014), therefore the relationship with political rights appears to be ambiguous. Similarly, whether the country is a democracy or an autocracy is not related to conflict, 1.4.

Finally, we hypothesize that the disease-conflict relationship depends on the provision of

[10] 84 slope for all countries with a $p - value < 0.1\%$ and 67 slope for Africa with a $p - value < 0.5\%$.
[11] 62 slope with $p - value < 5\%$ for all countries and 50 slope with $p - value < 5\%$ for Africa.

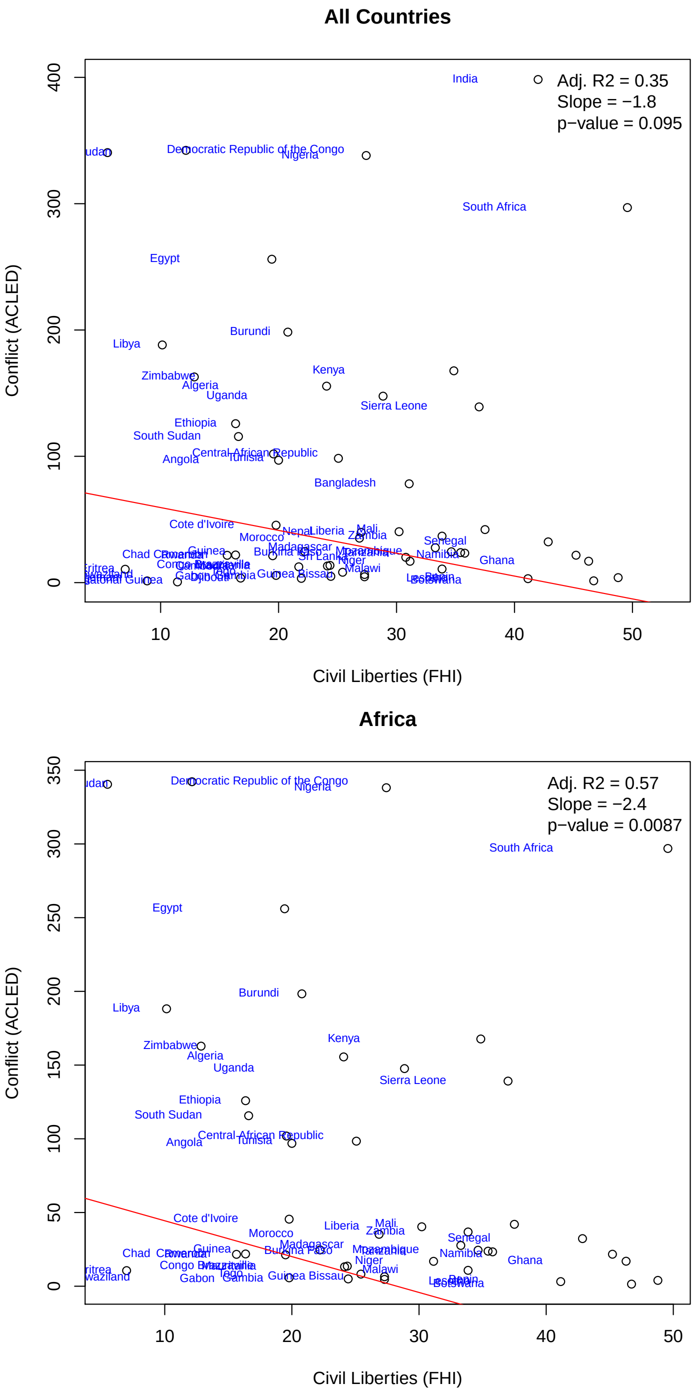
healthcare. Figure 1.5 gives suggestive evidence in this direction. In particular, it shows a negative relationship between public health expenditure and conflict, and a positive relationship between private health expenditure, both of which are weak and not statistically significant. Health expenditure is expressed as % of GDP and the scatter plots condition on population and income per capita. This evidence would be consistent with private health expenditure, which includes charitable donations, being disbursed during disease outbreaks, which are correlated with conflict, while public health expenditure reflects the amount of preventive public healthcare invested in a given country. In the next Section we will study whether health expenditure affects the disease-conflict relationship.

Figure 1.1: Disease outbreaks and Conflict incidence



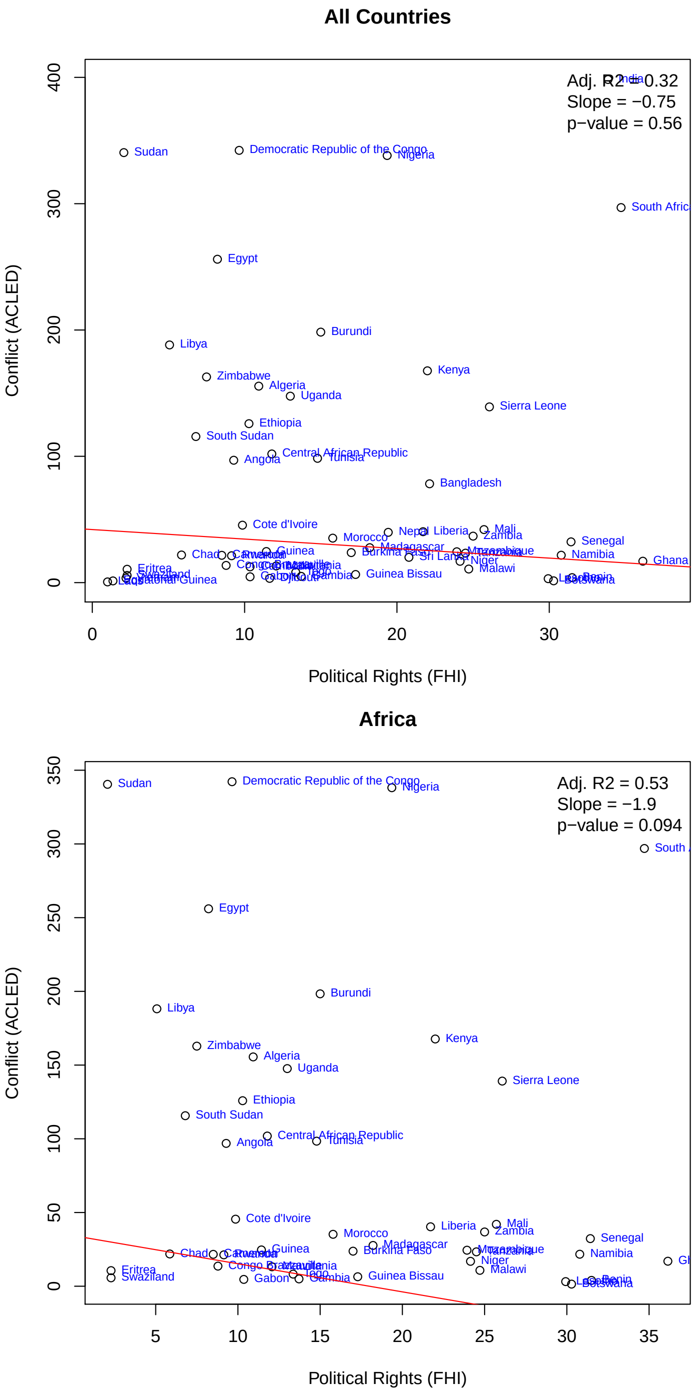
Notes: Conditional on average population, GDP in 2010 constant US dollars (World Bank/OECD). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). Disease outbreak alerts (excluding updates) (WHO). The slope is conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD). Observations: 67 countries over 1997-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico (excluding the outliers Pakistan and Somalia).

Figure 1.2: Civil liberties and Conflict incidence



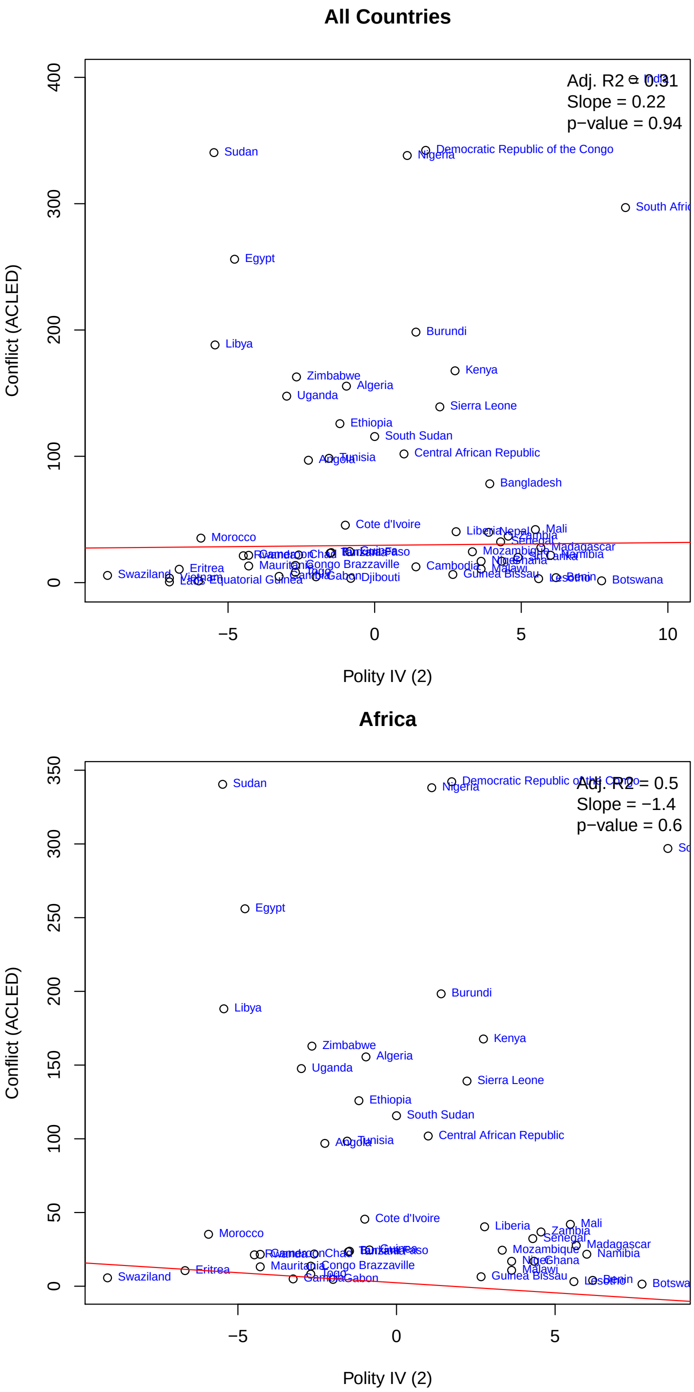
Notes: Conditional on average population, GDP in 2010 constant US dollars (World Bank/OECD) and new disease outbreaks (WHO). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). *Civil Liberties*: civil liberties, aggregating freedom of expression and belief, associational rights, rule of law, individual rights, with higher values indicating more liberties or rights (Freedom House Index). Observations: 67 countries over 1997-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico.

Figure 1.3: Political rights and Conflict incidence



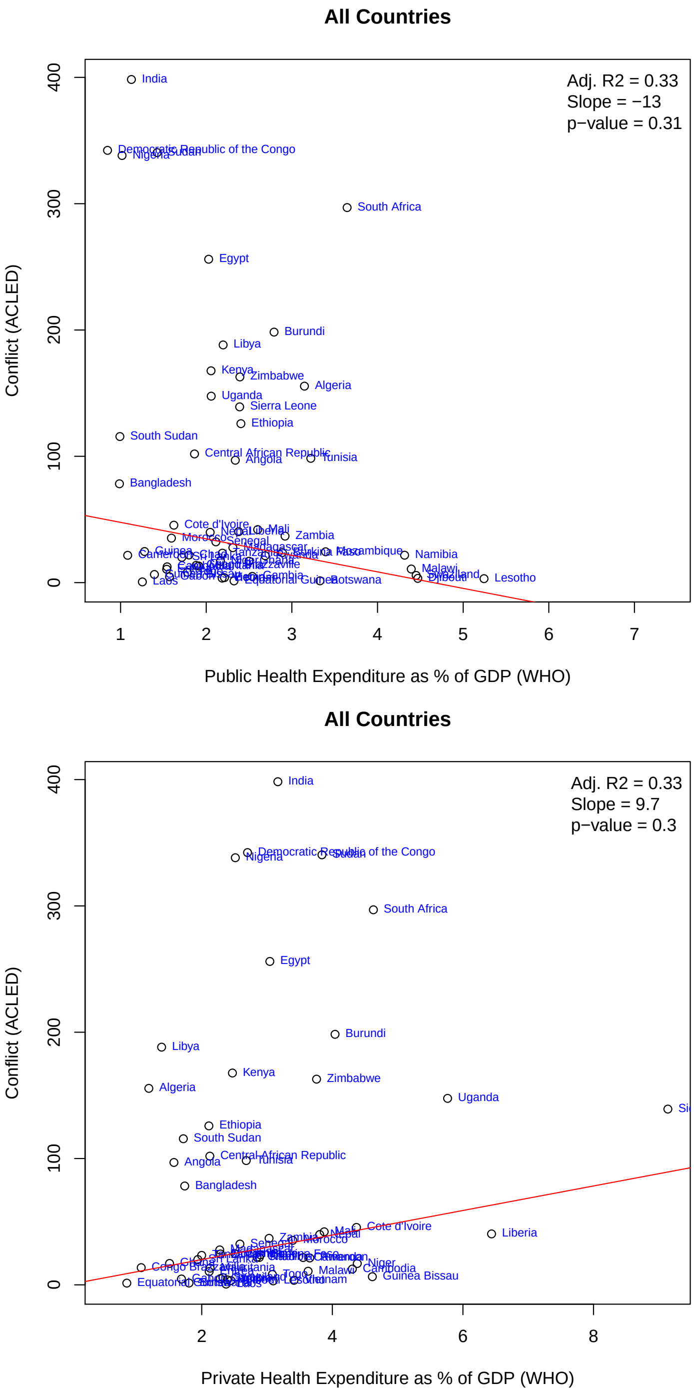
Notes: Conditional on average population, GDP in 2010 constant US dollars (World Bank/OECD) and new disease outbreaks (WHO). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). *Political Rights*: electoral process, political pluralism and participation, functioning government, with higher values indicating more liberties or rights (Freedom House Index). Observations: 67 countries over 1997-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico.

Figure 1.4: Democratic Institutions (Polity IV) and Conflict incidence



Notes: Conditional on average population, GDP in 2010 constant US dollars (World Bank/OECD) and new disease outbreaks (WHO). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). *Polity IV*: "autocracies" (-10 to -6), "anocracies" (-5 to +5 and three special values: -66, -77 and -88), and "democracies" (+6 to +10); *Polity IV* (2): replaces the three special systems with value 0, (Center for Systemic Peace). Observations: 67 countries over 1997-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico.

Figure 1.5: Health Expenditure and Conflict incidence



Notes: Conditional on average population, GDP in 2010 constant US dollars (World Bank/OECD). Data Sources: *Conflicts*: average number of yearly Conflicts (ACLED). *Public Health Expenditure*: recurrent and capital spending from government budgets, external borrowings and grants (incl. donations from international agencies / NGOs), and social (or compulsory) health insurance funds. *Private Health Expenditure*: direct household (out-of-pocket) spending, private insurance, charitable donations, and direct service payments by private corporations (WHO). Observations: 67 countries over 1997-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico (excluding the outliers Pakistan and Somalia).

1.4 Event study

Disease and Conflict

This Section uses an event study design to explore the effect of disease outbreaks this year in a given country on conflict incidence in the following year. The analysis is intended as exploratory and descriptive of the main patterns found throughout countries and diseases. Equation (1.1) summarizes the empirical strategy.

$$Conflict_{i,t+1} = \beta \ DiseaseOutbreak_{i,t} + \mathbf{X}_{i,t} \ \Gamma + \alpha_i + \lambda_t + \mu_{r,t} + \epsilon_{i,t} \tag{1.1}$$

The effect of interest β measures the predictive power of a new disease outbreak starting last year t in a given country i on number of conflicts in the next year, conditional on covariates $\mathbf{X}_{i,t}$, country α_i, year λ_t and continent×year $\mu_{r,t}$ fixed effects.

The outcomes of interest are either the total number of conflicts, without making a distinction between conflict events, riots in particular, which is a violent form of protest, and conflicts specifically described as disease-motivated. *DiseaseOutbreak* is the number of new disease outbreak alerts published by the WHO. We exclude outbreak alerts that are repetitive (i.e. they are identical to an immediately preceding disease outbreak alert), in order to reduce the potential problem that our effect captures the international interest conceded to a given disease outbreak.

$\mathbf{X}_{i,t}$ is the information set available at t. It includes disease outbreaks, population and income in the previous year $(t-1)$. We control for correlates in the previous year in order to avoid controlling for a variable that is potentially affected by our treatment of interest, disease outbreaks at t. Disease outbreaks in the past year are included as controls in order to account as far as possible for omitted variables affecting the spread of disease. This means that β will capture the effect of new disease outbreaks at t, net of other things that affected the likelihood of disease spread over the past year. Standard errors are clustered by country, the cross-sectional unit of observation. We study 69 countries over 20 years, from 1997-2016.

There are several reasons why equation (1.1) is not a causal study. First, the measure of disease outbreak alerts are not patient records and conflict incidence can either reduce or increase the salience of disease outbreaks for the WHO. Secondly, we are pooling various diseases that can themselves be an outcome of previous conflicts and that potentially exhibit different spreading dynamics. Thirdly, there are omitted variables that could affect this relationship at the year by country level. We can somewhat reduce these concerns by studying the full event study, looking at the correlation at different lags and leads of the outcome, i.e. equation (1.2).

$$Conflict_{i,t+h} = \beta_h \; DiseaseOutbreak_{i,t} + \mathbf{X}_{i,t+h-1} \; \Gamma + \alpha_i + \lambda_t + \mu_{r,t} + \epsilon_{i,t} \tag{1.2}$$

for all $h \in [-4, +4]$

If new disease outbreaks increase the likelihood of conflict, $\beta_h > 0$ for $h > 0$. If conflict generates new disease outbreaks, $\beta_h > 0$ for $h < 0$. If we find contemporaneous effects, $\beta_0 > 0$, it is hard to say in this setting which causes the other. Note that $\mathbf{X}_{i,t+h-1}$ controls for disease outbreaks prior to $(t + h)$.

Institutions

We next study the hypothesis that the disease-conflict relationship changes with better institutions. Firstly, better institutions, such as greater civil liberties or political rights could make conflict a relatively sub-optimal solution to solve a bargaining process between two groups[12]. Secondly, if some types of conflict, such as civil violence, are a form of expression of social dis-contempt, we should expect freedom of expression to be a substitute

[12]The measure of institutions used is the Freedom House Index on civil rights or political rights and the Polity IV score in the past year. Greater values of these scores indicate better institutions. Where civil liberties aggregate freedom of expression and belief, associational rights, rule of law, individual rights; and political rights aggregate the right to an electoral process, political pluralism and participation, a functioning government. Higher values indicate more liberties or rights (Freedom House Index). *Polity IV* (2) captures this regime authority spectrum on a 21-point scale ranging from -10 (autocracy) to +10 (consolidated democracy) (Center for Systemic Peace).

of civil violence. The empirical strategy is summarized in equation (1.3).

$$\begin{aligned} Conflict_{i,t+1} &= \beta\ DiseaseOutbreak_{i,t} + \gamma\ Institutions_i^{High} \\ &+ \delta\ DiseaseOutbreak_{i,t} \times Institutions_i^{High} + \mathbf{X}_{i,t}\ \Gamma + \alpha_i + \lambda_t + \mu_{r,t} + \epsilon_{i,t} \end{aligned} \tag{1.3}$$

Where $Institutions_i^{High}$ is a dummy variable taking value 1 if the average measure of institutions for a given country over time is above the mean for all countries. The effect of interest is δ, which measures the change in the effect of disease outbreaks on conflict incidence, for countries with above average level of institutions, conditional on covariates. The measure of institutions is the average over time of the Freedom House Index on civil rights or political rights and the Polity IV score. Greater values of these scores indicate better institutions[13]. The covariates included in $\mathbf{X}_{i,t}$ are the same as in equation (1.1) above, except that disease outbreaks at $(t-1)$ are interacted with *Institutions*.

Public Health Expenditure

Finally we also test the hypothesis that the effect of disease outbreaks on civil conflict is mitigated by the provision of health care. Health care reduces the detrimental effect of a disease by reducing morbidity and mortality. Therefore, if the link between epidemics and conflict is driven by social unrest or demand for public goods, we expect the effect of disease outbreaks on conflict incidence to be smaller for greater availability of health care. As a proxy for health care we use the % of GDP committed to health expenditure in the past year. The empirical strategy is summarized in equation (1.4).

$$\begin{aligned} Conflict_{i,t+1} &= \beta\ DiseaseOutbreak_{i,t} + \gamma\ HealthExpenditure_{i,t-1} \\ &+ \delta\ DiseaseOutbreak_{i,t} \times HealthExpenditure_{i,t-1} + \mathbf{X}_{i,t}\ \Gamma + \alpha_i + \lambda_t + \mu_{r,t} + \epsilon_{i,t} \end{aligned} \tag{1.4}$$

[13] *Civil Liberties*: civil liberties, aggregating freedom of expression and belief, associational rights, rule of law, individual rights; *Political Rights*: electoral process, political pluralism and participation, functioning government, with higher values indicating more liberties or rights (Freedom House Index); *Polity IV* (2): captures this regime authority spectrum on a 21-point scale ranging from -10 (autocracy) to +10 (consolidated democracy) (Center for Systemic Peace).

The effect of interest is δ, which measures the change in the effect of disease outbreaks on conflict incidence, due to an increase in health expenditure in the past year, conditional on covariates. The measure of health expenditure is the % of GDP committed in the past year[14]. The covariates included in $\mathbf{X}_{i,t}$ are the same as in equation (1.1) above, but we also add health expenditure in the previous year $(t-1)$ and both population, income and prior disease outbreaks at $(t-1)$ are interacted with health expenditure at $(t-1)$.

Unless health expenditure perfectly predicts new disease outbreaks, other than due to prior disease outbreaks, δ should be a satisfactory approximation of the mitigating effect of health expenditure on the disease-conflict relationship.

Results

The results show a positive relationship between new disease outbreaks and conflict incidents in the following years. The effect is not precisely estimated for conflict incidents overall until three years ahead, Table 1.2, but it is significant at the 5% level for riots or for health or disease-related conflicts in the next year and in the following years, Tables 1.3-1.4. A new disease outbreak in a given year is followed by 66 additional riots next year or a 15% increase and by 2.5 additional health or disease-related conflicts, or a 12% increase in these events[15]. With an average of 0.4 disease outbreak alerts each year, Table 1.1, this suggests that an average of 26 riots follow disease outbreaks each year and only 1 of them is explicitly disease or health-related according to the newspapers reporting on the event. Results for an alternative specification with a count data model is shown in Table A.13. The effect of disease outbreaks on conflict incidence in this specification is more precisely estimated.

When accounting for heterogeneous effects by institutions or health expenditure the correlation between epidemics and conflict is larger and more precisely estimated, suggesting

[14] We study either total, private or public health expenditure.

[15] Observations are weighted by population. Since population changes over time we use the first available population data. Results are equivalent when using the average population over the time period.

that these are potentially important mechanisms underlying this relationship, Tables 1.5 and A.1-A.2 and Figures 1.6 and A.2-A.3. The effect of disease outbreaks on conflict incidence disappears in countries with above average political rights or civil liberties[16]. The effect is somewhat larger in countries that are democratic, compared to autocratic countries, but the difference is not statistically different from zero. It is smaller in countries with greater freedom of expression, but the effect is not statistically different from zero. We also see a smaller but not statistically significant effect of disease outbreaks on conflict incidence when a greater proportion of the GDP is dedicated to health expenditure in the past year.

These patterns are suggestive of important heterogeneities across political institutions and public policies underlying in the effect of shocks such as epidemics on conflict incidence in developing countries.

Table 1.2: Event study of Disease outbreaks on Conflict

	Conflicts								
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	7.260	-22.56	13.38	-13.29	-5.629	52.28	130.0	242.1*	50.27
	(14.16)	(23.96)	(15.97)	(18.28)	(49.48)	(34.48)	(88.48)	(139.68)	(65.64)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.748	0.651	0.680	0.669	0.889	0.881	0.870	0.873	0.889
Mean	65.10	80.70	95.54	116.7	516.5	555.5	602.0	658.9	727.6

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), Disease(t+j-1), Disease(t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico (excluding Pakistan, Somalia and South Sudan).

[16] This is not apparent when using within country variation of institutions fluctuating over time instead of the country average, Tables A.8, A.6

Table 1.3: Event study of Disease outbreaks on Riots

	Conflicts								
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	5.988	-20.02	11.03	0.148	4.338	66.25**	127.3	212.3	48.45
	(6.62)	(17.56)	(12.03)	(11.18)	(44.37)	(30.54)	(80.66)	(128.32)	(58.73)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.559	0.482	0.547	0.541	0.896	0.886	0.874	0.876	0.893
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), Disease(t+j-1), Disease(t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico (excluding Pakistan, Somalia and South Sudan).

Table 1.4: Event study of Disease outbreaks on Health or Disease-related Conflict

	Conflicts								
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	0.278	-0.542	0.109	-0.455	-0.580	2.438**	5.839*	10.72*	2.496
	(0.22)	(0.46)	(0.42)	(0.58)	(1.99)	(1.15)	(3.43)	(6.35)	(2.94)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.546	0.556	0.590	0.479	0.885	0.876	0.864	0.865	0.880
Mean	0.845	1.128	1.466	2.316	19.18	20.76	22.61	24.85	27.58

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), Disease(t+j-1), Disease(t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico (excluding Pakistan, Somalia and South Sudan).

1.5 Conclusion

The purpose of this chapter is to show a novel empirical pattern found across countries and disease outbreaks, namely that while disease outbreaks are associated with greater likelihood of conflict, this relationship highly depends on political institutions and polices, such as public health expenditure. The second chapter seeks to causally identify the impact of an epidemic on civil violence and the role of the state response and trust in authorities in determining this relationship. The third chapter, on the other hand, studies the effects of a particular policy, namely local media, on the spread of an epidemic, and explores its role as a coordination device to change cultural practices.

Table 1.5: Event study of Disease outbreaks on Riots
Heterogeneous effects by Institutions / Health Expenditure

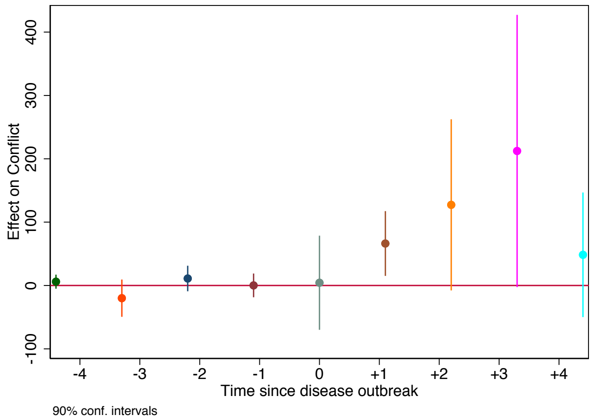
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
disesase(t)	12.58	67.34**	66.25**	57.06*	177.9**	139.9***	63.65	74.04**
	(19.56)	(31.09)	(30.54)	(31.12)	(74.78)	(35.59)	(49.89)	(32.31)
disesase(t) × Polity IV^{High}				28.28				
				(90.63)				
disesase(t) × Political Rights^{High}					-308.6**			
					(133.63)			
disesase(t) × Civil Liberties^{High}						-127.1***		
						(44.17)		
disesase(t) × Freedom of Expression^{High}							-16.13	
							(65.35)	
disesase(t) × Health Expenditure (t-1)								-14.88
								(21.01)
Observations	648	577	577	577	577	577	577	577
R-squared	0.814	0.886	0.886	0.886	0.901	0.887	0.888	0.887
Mean	427.6							
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Year × Continent FE	Y	Y	Y	Y	Y	Y	Y	Y
Population(t-1),GDP(t-1)		Y	Y	Y	Y	Y	Y	Y
disease(t-1)			Y	Y	Y	Y	Y	Y
(1, disease(t-1)) × Institutions(t-1)				Y	Y	Y	Y	
(1, disease(t-1)) × Health Expenditure(t-1)								Y

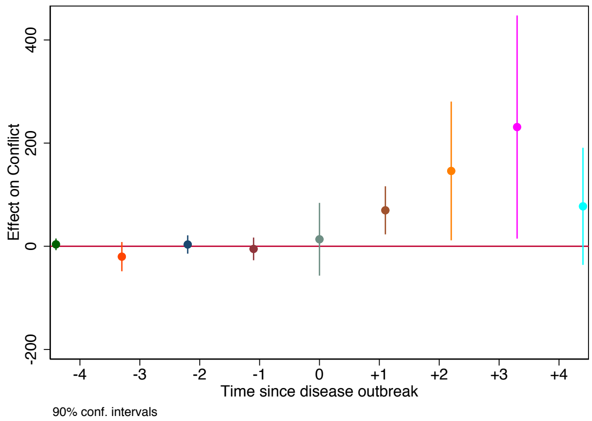
(Robust SE) clustered by country
Where Institutions are demeaned variables.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD) at $(t-1)$, and disease outbreaks one year before and also at $(t-1)$. Weighted by average population over the sample period. For full specification equation (1.3). Definitions: *Conflicts*: disease-motivated conflicts according to the description of the event (ACLED). Disease outbreak alerts (excluding updates) (WHO). *Civil Liberties*: civil liberties, aggregating freedom of expression and belief, associational rights, rule of law, individual rights; *Political Rights*: electoral process, political pluralism and participation, functioning government, with higher values indicating more liberties or rights (Freedom House Index); *Polity IV* (2): captures this regime authority spectrum on a 21-point scale ranging from -10 (autocracy) to +10 (consolidated democracy) (Center for Systemic Peace). Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico (excluding Somalia, Pakistan (outliers) and South Sudan (incomplete data on civil liberties)).

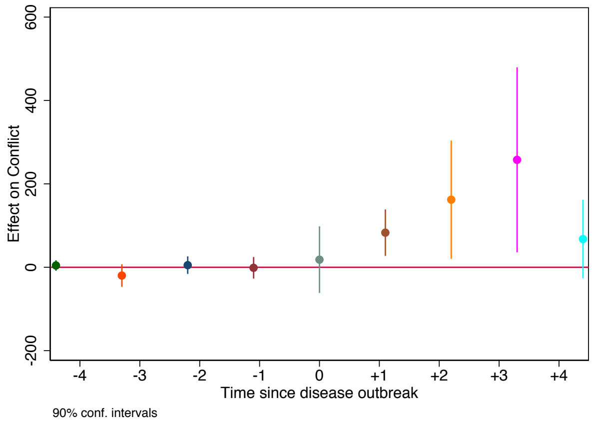
Figure 1.6: Event study of Disease outbreaks on Riots

Outcome: Conflict events in year t





Conditional on civil liberties (demeaned) × (1, disease outbreaks)



Conditional on political rights (demeaned) × (1, disease outbreaks)

Notes: Conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD) at $(t-1)$, and disease outbreaks one year before and also at $(t-1)$. Weighted by average population over the sample period. For full specification equation (1.2). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). Disease-motivated conflicts according to the description of the event. Disease outbreak alerts (excluding updates) (WHO). Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico.

Chapter 2

Epidemics and Conflict: Evidence from the Ebola outbreak in Western Africa

"If the sun refuses to rise we will make it rise."

Chimamanda Ngozi Adichie, *Half of a Yellow Sun*

2.1 Introduction

Numerous acts of civil violence are reported in newspapers following the spread of epidemics throughout the African continent today[1]. Mobs, riots and attacks often target government authorities, health personnel and social workers aiming to contain an epidemic[2]. Since these episodes are especially likely to happen in weak institutional settings, under the presence of latent conflict, and poverty and conflict can facilitate the spread of disease, establishing causal evidence is difficult, yet of great policy relevance. Identifying the drivers of civil violence in the context of an epidemic and the type of state response

[1] We have identified riots, protests and violence against civilians following the spread of cholera, malaria, Ebola, HIV/AIDS, or unidentified diseases, in Congo, DRC, Kenya, Nigeria, Mozambique, Uganda, Tunisia, Somalia, South Africa, from newspaper reports in the Armed Conflict Location and Event Data Project, 1997-2015.

[2] Examples are provided in the Supplementary Appendix Table D.3.

that fuels or mitigates this effect is ever more important for policy makers, as infectious disease outbreaks are on the rise in developing regions and greater humanitarian aid is needed to respond to them (Jones et al., 2008).

In this paper we seek to identify the impact of an epidemic on civil violence and the role of the state response and trust in authorities in determining this relationship. In doing so we aim to learn about determinants of conflict and in particular the part played by perceived state coercion and demand for public goods in fueling social unrest. We also study the consequences for long-run trust in institutions.

The main contribution of this paper is to develop strategies to identify both the impact of an epidemic on the likelihood of conflict and precise channels underlying this effect. We also show long-run consequences by studying its impacts on trust in institutions. We study the state response or emergency assistance and provide new evidence on drivers of civil violence. We do this in the context of the Ebola epidemic in Western Africa in 2014-15, described as the largest, most severe and most complex outbreak in the history of the disease (WHO, 2015). The outbreak was a major shock that generated a great influx of state capacity[3], through foreign aid, and required the adoption of new medical technologies, as well as a change in cultural practices to halt the spread of the disease. Numerous riots, protests and violence against government officials, medical personnel and social workers were reported in newspapers. We exploit detailed data available at weekly and localized level on Ebola infections, conflict events and intervention measures, combined with the precise dynamics of the Ebola Virus Disease (EVD) and the timing of distinct intervention measures to identify the impact of the epidemic on civil violence for different containment efforts in the countries most affected by the epidemic, namely Guinea, Liberia and Sierra Leone. The setting further allows us to track the impact of the

[3] Including financial resources, medical technology and infrastructure and military aid, coordinated under the auspices of the World Health Organization (WHO). The total worth of direct and in-kind contributions to WHO for the Ebola response was US$459 million from over 60 donors between March 2014 and 22 April 2016, `www.who.int/csr/disease/ebola/funding/en` updated April 2016. We see this as a permanent shock in state capacity, since it led to an improved public health system that is now ready to contain future Ebola outbreaks. Moreover, community responses were key in containing the epidemic and this experience can have permanent effects on containing future disease outbreaks.

epidemic shock on civil violence under varying levels of ethnic diversity, religious beliefs and trust and measure long-run impacts on trust in institutions.

Epidemics affect the relationship between civilians or between civilians and the state. These changes can lead to social unrest. We conjecture that an epidemic in which the state intervenes or is expected to intervene changes citizens' perception of the state and demands from it in at least three ways. First, it leads the state to adopt coercive measures, in order to halt contagion. Second, it generates a demand for public goods, as people need health treatment. Third, it requires a change in cultural practices, such as burial practices, and these are induced by state authorities. We hypothesize that these changes are important drivers of civil violence targeted against institutional authorities in the context of an epidemic, and whether they are perceived as threats and ultimately lead to civil conflict depends on beliefs, trust in institutions and the response of the state. Epidemics also tear families apart and affect the relationship between citizens, fearing contagion. In this paper we highlight the importance of institutional channels, those that are influenced by policy makers, through the choice of a particular emergency response. These mechanisms mean that epidemics are more likely to lead to civil conflict in weak institutional settings[4]. Moreover, they can deepen mistrust in institutions, therefore further weakening the state.

We test our hypotheses empirically and approach this by combining several data sources. The explanatory variable, the number of Ebola infections, are patient records from the World Health Organisation (WHO) and the National Ebola Response Ebola Center (NERC) in Sierra Leone. This data was collected in Guinea for Chapter 3 and for Sierra Leone it was shared by Fang et al. (2016). For Liberia we use publicly available data and additional data scraped from Situation Reports from the Liberian Ministry of Health. Our

[4]With low access to public goods, low trust in leaders and settings in which state coercion is perceived as illegitimate.

outcome variable are riots, protests and violence against civilians that are large enough to be recorded in local, national and international newspapers, provided by the Armed Conflict Location and Event Data Project[5]. The intervention measures were published during the Ebola outbreak to facilitate containment efforts by the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA), the Red Cross and the WHO. We also use two rounds of Afrobarometer survey data, pre and post-epidemic.

We use two main sources of variation to identify the impact of the epidemic on conflict incidence. First, the epidemic had a clear beginning, in December 2013, and a clear end, in April 2016. The timing and location of the first human being infected with the virus in Guinea is an exogenous shock, created by the very unlikely event of animal-to-human transmission. The geographic spread throughout the region, prior to significant control efforts is largely due to pre-existing road and trade networks, mobility patterns and population density. Despite enormous efforts by Medecins Sans Frontieres (MSF) to control the epidemic, their capacity was largely overwhelmed by the speed of the disease spreading throughout the region until the international community committed a large amount of resources eight to nine months after the patient zero was infected at the borders in the intersection of three countries. We exploit this in a difference-in-difference design to look at the overall impact of the epidemic on conflict incidence. We look at the change in civil violence taking place before and after the start of the epidemic, comparing places hit by Ebola with different levels of intensity measured by the cumulative number of cases at the end of the outbreak. The identification relies on a parallel trends assumption and the exogeneity of the first index case. We strengthen our identification to address the possibility of ex-post selection into treatment by instrumenting the end-level of Ebola in a given location with the geographic distance to the first index case.

Second, the virus spread from human-to-human through body fluids under precise dy-

[5]We also did the same exercise using as outcome variable social resistance data, which was scraped from Situation Reports during the Ebola outbreak collected in Guinea Chapter 3. We also find a positive impact of Ebola infections on social resistance using this measure. At this stage they are omitted from the paper.

namics that we know from the epidemic models and that we observe at weekly level for a given location. We use this high-frequency panel to identify the impacts of new infections on riots in subsequent weeks, conditional on time, location and month per region fixed effects[6]. Identification relies on the arrival of new cases being random with respect to conflict, conditional on fixed characteristics and past incidence. We use two instrumental variables strategies to strengthen our identification. First, we instrument the number of new infections in a given location by the turning on and off of the epidemic in neighboring locations, to ensure that our findings are not driven by time-varying confounders with persistent effects in a given location. Secondly, we construct a predicted Ebola measure from the medical literature that relies on the geographic position of each location, infections several periods in the past and fixed characteristics, with the aim to address the possibility of non-standard measurement error in infections.

To study the role of the state response in determining civil violence, we exploit an exogenous shock in state capacity, following the emergency assistance package. It included military aid, new medical technologies and improved public health systems[7]. This gives us precise timing and location of containment efforts that allow us to study the role of perceived state coercion and demand for public goods in generating civil conflict. The impact of military district quarantines is studied in a difference-in-difference setting relying on the timing being independent of predicted conflict and on a parallel trends assumption[8]. The role of demand for public goods is measured by looking at the differential impact of new Ebola infections on conflict incidence for locations with varying levels of demand for health facilities, before and after their implementation[9].

[6]This is robust to controlling for infections in contiguous weeks, cumulative infections or past conflict incidence.

[7]We see this as a permanent shock in state capacity, since the public surveillance and response system that was put in place in West Africa is now ready to contain future outbreaks. Moreover, community responses were key in containing the epidemic and this required mobilizing local communities, as well as learning, halting the spread of rumors and changing burial practices, salutation and improving hygiene. This experience can have permanent effects on containing future disease outbreaks.

[8]We provide evidence that this is the case by showing parallel trends prior to their implementation. We also restrict our sample to ever quarantined districts in an event study. The results are robust to conditioning on areas with sufficient level of epidemic incidence.

[9]The decision of the international community to intervene serves as a timing event that is exogenous with respect to the local spread of Ebola and conflict incidence. The end-level of public good provision

The impact of trust and beliefs in the relationship between epidemics and conflict is studied by looking at the impact of new infections on conflict incidence for areas with varying levels of trust, religiosity, ethnic diversity and other expected correlates of civil violence. We hypothesize that religious beliefs are a predictor of civil violence in the context of an epidemic, as it requires a change in cultural practices, which is more costly for these groups.

Finally, we study the effect of the epidemic on trust in institutions. We compare trust levels before and after the Ebola outbreak for locations with different levels of Ebola incidence and we also explore how this varies by religiosity[10]. If changes in cultural practices are a driver of civil violence in the context of an epidemic, we expect trust in institutional authorities to drop especially for communities with strong religious beliefs.

The results show that one new Ebola infection in 100'000 per capita increases the likelihood of conflict in the next period by 10% in a given location[11], from a baseline mean incidence of 0.013 at two-week level, for a given location[12]. Our estimates mean that moving from no cases to the average Ebola incidence for locations that were hit by the epidemic in the first year doubles conflict incidence in a matter of weeks[13]. The type of conflict that arises is subversive violence, since the object of attack are institutional and medical authorities.

The impacts of this epidemic shock on civil violence are localized and its biggest impacts occur at the peak of the international intervention. Military district quarantines have a large impact on increasing the likelihood of riots and protests, beyond the impact of new

is a measure of the ideal level of health centers if the great amount of financial aid was available at the beginning of the outbreak. We use this to study the impact of new infections on conflict incidence for varying levels of public good provision at the end of the outbreak, before and after the arrival of aid.

[10]We study religiosity as measured prior to the outbreak.

[11]Conflict is measured as the number of conflicts in 100'000 per capita in a given location. Ebola is measured at county, chiefdom and sub-prefecture level and conflict is measured at district, chiefdom and sub-prefecture level, for Liberia, Sierra Leone and Guinea, respectively.

[12]In our tables we look at the incidence of conflict in one million per capita to let the reading of the tables be easier, so the baseline incidence in that case is 0.13.

[13]The average Ebola incidence for locations that were already hit in 2014 is 8 cases in 100'000 per capita.

infections. Prior to the arrival of a significant amount of emergency assistance, areas with more end-level of public goods have higher conflict incidence as a consequence of new Ebola cases, and the opposite effect thereafter[14]. The results indicate that civil conflict is fueled by perceived state coercion and demand for public goods. Lower trust in leaders and strong religious beliefs makes civil violence more likely to arise as a consequence of new Ebola cases[15].

The epidemic further deepens mistrust in institutional authorities. Two years after the outbreak there are lower levels of trust across measures compared to pre-epidemic levels. In particular the epidemic led to lower trust levels for locations that were hardest hit by the epidemic, especially for strong religious communities, which face larger costs of cultural adaptation.

Literature

We seek to contribute to several sets of literature. This paper adds to the empirical literature on the determinants of conflict, thoroughly reviewed by Blattman and Miguel (2010)[16]. We contribute to recent evidence studying the impact of endemic diseases, pathogens and infectious diseases on conflict incidence. Cervellati et al. (2016) provide first evidence of vector-borne endemic diseases as drivers of civil conflict[17], using cross country variation in exposure to human pathogens. They suggest that the impact of endemic diseases on conflict incidence is a direct effect of health. Cervellati et al. (2017, 2018) investigate the effect of malaria on civil conflict in the African continent using

[14]This holds when controlling for cumulative cases or allowing for heterogeneous effects for locations with varying end-level Ebola.

[15]Areas with strong religious beliefs do not have higher rates of civil violence at baseline.

[16]This paper is most related to a large literature studying economic determinants of conflict (Fearon and Laitin, 2003; Miguel et al., 2004; Bellows and Miguel, 2006; Burke et al., 2009; Brückner and Ciccone, 2010; Bazzi and Blattman, 2014; Berman et al., 2017), as well as a literature studying the role of ethnic diversity as a correlate of civil violence, collective action and the provision of public goods (Easterly and Levine, 1997; Posner, 2004; Habyarimana et al., 2007; Esteban and Ray, 2008; Eifert et al., 2010; Glennerster et al., 2013).

[17]In some cases they are recurrently epidemic, such as malaria in some regions. Vector-borne diseases require vectors of transmission, which are living organisms that can transmit infectious diseases between humans or from animals to humans; for example mosquitoes.

data at sub-national grid-cells, studying long-term impacts, as well as effects at monthly frequency exploiting variation in climatic conditions favorable for the transmission of malaria[18]. They suggest a health shock and a negative income shock as potential mechanisms and find exploratory evidence on the role of anti-malarial policies in lowering conflict incidence. This paper contributes to the evidence on the impacts of infectious diseases on civil conflict, methodologically, as well as more deeply by providing precise mechanisms underlying this effect. Ebola is a virus, does not require a vector of transmission and it is not driven by climatic variation[19]. In this way we isolate the impact of an epidemic from climate shocks driving conflict (Hsiang et al., 2011, 2013; Harari and La Ferrara, 2013). The Ebola epidemic is sufficiently large to generate social distress, but it did not affect the population size significantly[20]. In our context we are therefore able to rule out the potential effect of the epidemic acting through population changes (Acemoglu et al., 2017). Most importantly, the Ebola epidemic provides a unique opportunity to study a new epidemic to a large region[21], track it from the first index case to the last contagion, study the role of the state response to it and provide precise mechanisms linking the impact of a major epidemic outbreak to civil conflict. We suggest that epidemics trigger civil conflict as they affect the relationship between civilians or between civilians and the state. In the case of the Ebola outbreak the major influx of emergency assistance allows us to study the role of the state response in fueling civil violence. In particular, we provide evidence of perceived state coercion and demand for public goods as drivers of subversive violence, contributing to the discussion on the role of state capacity as a determinant of conflict

[18]They exploit the fact that the specific features of the malaria epidemiology imply temporary spikes in malaria transmission risk that are related to weather conditions and confined in time and space.

[19]Humidity can help its transmission, but the spread of the virus is driven by the contact with the body fluids of an infected person. After the first index case from animal-to-human, the spread is exclusively through to human-to-human contact and is largely driven by proximity to the epicenter

[20]The deceased population is 0.05% of the total population in the three most affected countries over 2-3 years, compared to an annual population death rate of 1% in Guinea and Sierra Leone or 0.7% in Liberia (CIA World Factbook, 2017). The total cumulative number of Ebola infections was 0.13% of the total population, and 2% is the maximum cumulative percentage of infected people in one location over the 2-3 years.

[21]The three most affected countries in West Africa comprise a total population of 23 million people. Discovered in the 1970s, the Ebola virus has caused around twenty outbreaks to date, all in Africa, but this was its first time turning into an epidemic and it was the first time it hit West Africa, therefore constituting an unknown disease to the population affected.

(Fearon and Laitin, 2003). This further suggests that perceived state coercion and little sensitivity to local customs is a complementary explanation to the impact of humanitarian aid on civil conflict, other than aid stealing by armed groups (Nunn and Qian, 2014). We also highlight the importance of religious beliefs in triggering civil violence in the context of an epidemic, due to a greater cost of changing cultural practices. This is consistent with the role of religious beliefs in spreading rumors or exerting violence (Miguel, 2005). Finally, we show that the epidemic lowers trust in institutional authorities, especially for religious communities. This provides further evidence of epidemics triggering civil conflict through their impact on changing citizens' perception of the state and adds to the evidence on determinants of trust (Nunn and Wantchekon, 2011).

Secondly, this work contributes to a literature on the role of the spread of diseases for social and institutional change (Acemoglu and Robinson, 2001; Acemoglu et al., 2003; Young, 2005; Alsan, 2014). We zoom into the short-run dynamics of institutional change driven by an epidemic. Dittmar and Meisenzahl (2016) find that Plague outbreaks in 16th century Europe shifted local politics in a few years, creating salience for public goods, and this paper increases our understanding of this process in the short-run, showing how riots and protests might arise immediately to demand public goods. This is related to work on protests and institutional change that finds an effect of changing beliefs on protests and collective action (Barbera and Jackson, 2016; Cantoni et al., 2017). Our findings are consistent with evidence of low health uptake in developing contexts (Dupas, 2011; Greenwood et al., 2013; Alsan and Wanamaker, 2016) and resistance to adopting new medical technologies (Caprettini and Voth, 2017). By studying the behavioral response to emergency assistance, we contribute to evidence of institutional determinants of the spread of infectious diseases (Adda, 2016; Morse et al., 2016).

Finally, this paper contributes to a long discussion among historians, on the role of epidemics as social toxins. Historians have noted two distinct types of civil violence that emerged as a consequence of epidemic outbreaks. Some epidemics have led to violence against civilians, such as ethnic violence or targetted at victims of the disease, notoriously the Black death in 14th century Europe and to some extent also later Plagues, the US smallpox epidemic or the HIV/AIDS epidemic in the early 20th century (Cohn, 2016). Epidemics in such contexts have sparked ethnic violence that lasted for centuries through cultural persistence (Voigtländer and Voth, 2012; Jedwab et al., 2017). Other epidemics have led to subversive violence, targetting government authorities, medical personnel and social workers. This is the case of the Ebola outbreak in Western Africa, there is ample historical evidence of similar violence arising during epidemic outbreaks in Europe, Russia or North America[22], and is recurrent throughout epidemic outbreaks in the African continent today[23]. Evans (1988) notes that "the general coincidence of cholera epidemics with years of upheaval and revolution has proved too obvious to ignore", however the direction of causality remains to be demonstrated. This paper gives proof of an epidemic leading to subversive violence and precise channels underlying this effect[24]. We provide empirical evidence of institutional mechanisms linking epidemics to civil violence in weak institutional settings and its long-run effects on trust.

The paper is structured as follows. In the following Section 2.2, we provide a brief background on the Ebola outbreak. The data sources are described in Section 2.3. The empirical set-up and results are presented in Section 2.4. First, we search for causal evidence linking the epidemic to civil violence, Subsection 2.4.1. Second, we provide empirical evidence on drivers of civil violence, Subsection 2.4.2. Third, we show long-run impacts of the epidemic on trust, Subsection 2.4.3. Robustness checks are presented in Subsection 2.4.4. We conclude in Section 2.5.

[22]Cholera riots similar to the Ebola riots in Western Africa were the norm during the cholera outbreaks in 19-20th century Europe, North America and Russia. On further historical evidence of epidemics fueling civil violence, vid. Evans (1988); Voigtländer and Voth (2012); Cohn (2016); Richards (2016)

[23]See examples in the Supplementary Appendix Table D.3.

[24]Understanding what makes ethnic rather than subversive violence more likely to arise is an interesting question for future work. We do not have the counter-factual of ethnic violence in the case of the Ebola outbreak. Which type of civil violence arises could depend on the response by the state, as this can affect the salience of the out-group. A relevant theoretical framework is provided by Esteban and Ray (2008, 2011b).

2.2 Background

The Ebola virus disease (EVD) is a severe disease with a fatality rate varying from $25 - 90\%$ at different stages of the outbreak. The virus is transmitted through physical contact with the blood, organs, secrecations, or other body fluids of infected humans or animals, such as fruit bats or primates, as well as infected objects, such as needles and syringes. The disease is characterised by initial flu-like symptoms, which rapidly progress into vomiting, diarrhea, stomach pain and haemorrhage[25]. The incubation period, i.e. the time from infection with the virus to the onset of symptoms, is estimated at an average of 8-12 days in the 2014 Western African Ebola outbreak (Van Kerkhove et al., 2015), but it can potentially take up to 21 days. The virus can only be detected after symptoms arise, even in the laboratory, and it is hard to detect at early stages[26]. Infectiousness increases at later stages, with deceased bodies being the most contagious. Patients die within one or two weeks after onset of symptoms or recover becoming immune. Ebola survivors suffer with persistent medical conditions after recovery, including joint pain, lost of sight, headaches, and other chronic health issues, as well as social stigma.

Discovered in the 1970s, the Ebola virus has caused around twenty outbreaks to date, all in Africa, but this was its first time turning into an epidemic[27]. The 2014 West African Ebola epidemic is the largest in history, causing over over 28,600 infections and over 11,300 deaths, between December 2013 and April 2016[28]. Within less than a year the disease spread through Guinea, Liberia and Sierra Leone, small outbreaks reached Nigeria, Mali and a few cases were exported to Europe and the US. Halting an Ebola outbreak requires a

[25] `www.who.int/ebola` or `www.cdc.gov/vhf/ebola`

[26] "Diagnosing Ebola in a person who has been infected for only a few days may be complicated. The early symptoms of Ebola infection are difficult to distinguish from other, more common infectious diseases such as such as malaria, influenza, and typhoid fever. Ebola virus is detected in blood only after onset of symptoms, most notably fever, which accompany the rise in circulating virus, however, it may take up to 3 days after symptoms begin for the virus to reach detectable levels." from Centers for Disease Control and Prevention
`http://www.cdc.gov/vhf/ebola/healthcare-us/laboratories/specimens.html`

[27] Definition of *epidemic* : affecting or tending to affect a disproportionately large number of individuals within a population, community, or region at the same time

[28] `http://www.who.int/csr/disease/ebola/en/`, accessed April 1, 2017.

great effort to treat symptomatic individuals, isolate infected people, trace their contacts, ensure safe burials and change population behaviors towards protective habits (Fast et al., 2014). This proved to be especially difficult in the present context of weak state capacity, slow international response, unfamiliarity with the disease and religious or cultural habits that facilitated the spread, especially through traditional burials.

Evidence suggests that the first index case[29] occurred in the Forest region in Guinea in December 2013 at the borders of Liberia and Sierra Leone. Subsequent cases spread exclusively through human-to-human contact. For eight to nine months these countries with very weak health systems and state capacity, tried to deal with the outbreak, with soaring death rates. Medecins Sans Frontieres (MSF), who scaled up their intervention, called it an 'unprecedented Ebola epidemic' already by end of March 2014. It was not until August 2014 that the World Health Organisation (WHO) declared it an 'international public health emergency', followed by financial aid from international donors. By the time international aid reached the affected countries, over 4,000 cases had been confirmed. International aid coordinated by the WHO implemented specialized medical infrastructure, contact tracing, surveillance systems and awareness raising campaigns. The peak of the outbreak due to the effectiveness of the interventions was reached by the end of 2014. The outbreak came to an end mid-2015, except for Guinea, which had a significant amount of cases until end of 2015. New infections still appeared in April 2016, but at that point new medical infrastructure and surveillance systems were in place to avoid another major outbreak and the epidemic was officially declared to an end in the summer of 2016.

Numerous riots, protests and violence erupted to counter medical interventions that were opposed by the civilian population. A few examples of violence during the Ebola outbreak include (Cohn and Kutalek, 2016) :

> "[In Guinea], Macenta on 5 April 2014, urban youth attacked the towns first [Ebola] clinic constructed a week earlier, and threatened fifty or more of

[29] The first contagion to humans is zoonotic, i.e. entering in contact with a reservoir host, such as bats, for instance by eating rare bush meat.

> the centres personnel. The protesters claimed [Ebola] did not exist or was spread by outsiders [...]. Then on 16 September, at Womey, West Africa experienced its worst [Ebola] atrocity when 8 members of a high-level delegation of doctors, politicians, and journalists were killed and their bodies dumped in a latrine [...]. At Matainkay, east of Freetown, Sierra Leone, on 20 September 2014, villagers assailed health workers while they buried [Ebola] victims, and in December, the Red Cross reported further attacks on their burial teams with damages to their vehicles. In Liberia at Westpoint, a poor township in Monrovia, an angry mob overran a health care facility, brought out all patients isolated there and looted the clinic."

Containment efforts were opposed by the civilian population either because they were coercive, such as military quarantines or forced detainment in Ebola treatment units (ETUs); the intentions of emergency assistance were misunderstood, through the spread of rumors; or they went against people's most fundamental beliefs, surrounding the burial of the deceased family members. This allows us to identify three main sources of distress associated to an epidemic.

The first source of distress is military or police action. Their activity included maintaining checkpoints, patrolling country and locality borders, enforcing village-level and district-wide quarantines, and taking punitive measures against individuals found in violation of government mandates for burials, case reporting, and caregiving[30]. Military district-quarantines, curfews or area blockades, for instance, meant that people could not leave a given area, while knowing that they are surrounded by other people infected with Ebola. The population size of an area blockaded varied. It could affect a village, chiefdom or a whole district[31]. The decision is taken in some cases at government level, sometimes at chiefdom level.

[30] In some cases security forces were doing required public health actions, in others they showed an abuse of power. In either case, these activities received a variety of responses, from acceptance to outright resistance (Hofman and Au, 2017).

[31] In our dataset the average size of a geographic unit quarantined is 50'000 people.

The second source of distress is demand for health treatment, on one hand, and rumors surrounding it, on the other. Ebola patients need to be isolated to avoid contagion and treatment requires special equipment, including the use of personal protective equipment (PPE) by doctors. This meant that patients could not be treated in hospitals and instead required the establishment of ad-hoc health centers, known as Ebola treatment units (ETUs). According to our interviews with social workers in Guinea, the biggest source of rumors and conspiracy theories was around what was happening inside ETUs[32]. Given that Ebola was a new, unknown disease to the region, that early Ebola symptoms are very similar to other endemic diseases in the region and that people died in ETUs with a very high fatality rate at the beginning at the outbreak, it is not surprising that rumors spread[33]. At later stages of the outbreak, when the public health systems were improved, including the establishment of laboratories that allowed for rapid testing, death rates went down and the benefit of seeking treatment in an ETU became prevalent. In some cases an alternative method emerged, known as Community care centers (CCCs), for first patient care of suspect patients. These were opened spontaneously by the communities and led by traditional caregivers, rather than professional staff.

Third, changes in cultural practices were associated with social unrest. Traditional burial practices involved washing the deceased by close family members. Since the Ebola virus disease is most infectious in dead bodies, changing this practice was a first priority. In Liberia cremations were imposed (Richards, 2016) and in the other countries the first attempt was to impose safe burials, which did not allow for traditional or religious customs. The Red Cross and Red Crescent Movement, who were in charge of conducting safe burial practices, received significant violent opposition. In Guinea alone, reported attacks against Red Cross volunteers averaged ten per month in the last six months of 2014[34]. Safe

[32] According to their accounts, an important way to halt the spread of rumors was for family members to come and see what was happening inside the ETUs.

[33] In pure observational probabilistic terms entering an ETU was a death sentence at the start of the outbreak, especially for patients that arrived when symptoms were already advanced.

[34] IFRC, website. The had to use personal protective equipment (PPE) to avoid their own contagion with the virus, which has a very impressive effect, as the whole body is covered and you are not able to see the face of the person.

burials were progressively adapted to local customs, such as involving religious leaders, leading to what became known as safe and dignified burials.

Social unrest or resistance against the health interventions, on the other hand, can lead to lower health uptake and affect the spread of the disease. Anthropology studies, medical reports (Moon, 2015) and own-collected evidence from interviewing health personnel, social workers and public officials in Guinea, suggest that informing, persuading and involving communities, religious and local leaders in containment activities was key for the success of the intervention. Chapter 3 shows that places that had access to a prolonged campaign from local radios designed to stop the spread of Ebola rumors in Guinea had a decrease in social unrest and a drop in Ebola cases seven months after the start of the campaign, compared to other areas with access to the same campaign from distant communities or to areas with access to national or private radio stations.

2.3 Data

The explanatory variable, the number of Ebola infections, originates from patient records from the World Health Organisation (WHO) and the National Ebola Response Ebola Center (NERC) in Sierra Leone. The number of Ebola infected cases was collected in Guinea for Chapter 3 and for Sierra Leone it was shared by Fang et al. (2016). For Liberia we use publicly available data from WHO and additional data scraped from Situation Reports from the Liberian Ministry of Health. Ebola cases can be either suspect, probable or confirmed, depending on the stage at which patients have been identified, based on symptoms or laboratory testing. We exclude suspect cases, since these are cases that have not been evaluated by a clinician[35]. Infections are reported at weekly level and the date corresponds to the actual or estimated date of symptom onset. Hence, these are contagions that necessarily occurred prior to the week of report, most likely in a time

[35] This is strategy is consistent with the reporting practice of the WHO, which publish data of confirmed and probable cases only. In addition, for Liberia, our measure of suspect cases might contain errors in timing or double counting, since these are scraped from Situation Reports, published at the time, rather than from the Patient database. The results are qualitatively similar when adding suspect cases.

window of 1-2 weeks before. We collapse the data to two-week windows in order to take into account the possible time-span from contagion to symptom onset. Cases are recorded at the level of sub-prefecture for Guinea, chiefdom for Sierra Leone and county for Liberia. Our main measure of infections are new Ebola infections in 100'000 per capita in a given geographical unit (507) over two weeks (115) from January 2012 - May 2016.

Our outcome of interest, conflict incidence, is constructed using the Armed Conflict Location and Event Data Project[36] Version 6 - 2015 and Realtime data 2016, which collects data on intergroup conflict from local and international newspapers, coding the exact date, geographic coordinates, type of conflict event, actors involved, number of fatalities, news source and description found in the newspaper[37]. We consider all conflict types, irrespective of the number of fatalities involved. During the sample period, the most common conflict events are intra-state conflict, i.e. civil conflicts, including riots, protests and violence against civilians. We aggregate conflict events at the level of sub-prefecture for Guinea, chiefdom for Sierra Leone and district for Liberia. For Liberia, this is a more disaggregated level than the number of Ebola cases. Since we use population weights in all our specifications, results are unchanged if we aggregate the number of conflicts to county level for Liberia. The advantage to use the lowest possible level of disaggregation, is that we have more variation in pre-determined characteristics to study heterogeneous effects. Our main outcome variable is the number of conflicts in 1'000'000 per capita in a given geographic unit (573) over two weeks (115) from January 2012 - May 2016.

Military district-quarantines and movement restrictions at given dates and locations were collected by the Red Cross and Red Crescent Movement. We consider that a given location is quarantined if the chiefdom or district is quarantined. Given this definition, the average size of a quarantined area in our dataset is 50'000 people, compared to an average population of 40'000 people. The implementation of laboratories and health treatment

[36] www.acleddata.com

[37] We also did the same exercise using as outcome variable social resistance data, which was scraped from Situation Reports during the Ebola outbreak collected in Guinea for Chapter 3. We also find a positive impact of Ebola infections on social resistance using this measure. At this stage they are omitted from the paper.

units, such as Community care centers (CCCs) and Ebola Treatment Units (ETUs) are from the WHO and the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA). Election dates and results to study the role of political grievances in fueling civil violence were scraped from newspapers. To study the possibility of economic mechanisms being at play we use food price statistics collected by Glennerster et al. (2016).

Population data is taken from the 2014 census in Guinea and Sierra Leone. We projected the 2008 census to estimate the population in 2014 for Liberia, based on a combination of prior population growth rates for each district and the growth rate for Liberia overall from 2008 to 2014. To study heterogeneous effects we use predetermined covariates prior to the start of the outbreak. Household survey data are taken from the Afrobarometer, Rounds 5, 2012-2013 and 6, 2015-2016. We construct averages for each variable by sub-prefecture, chiefdom and district for the respective countries.

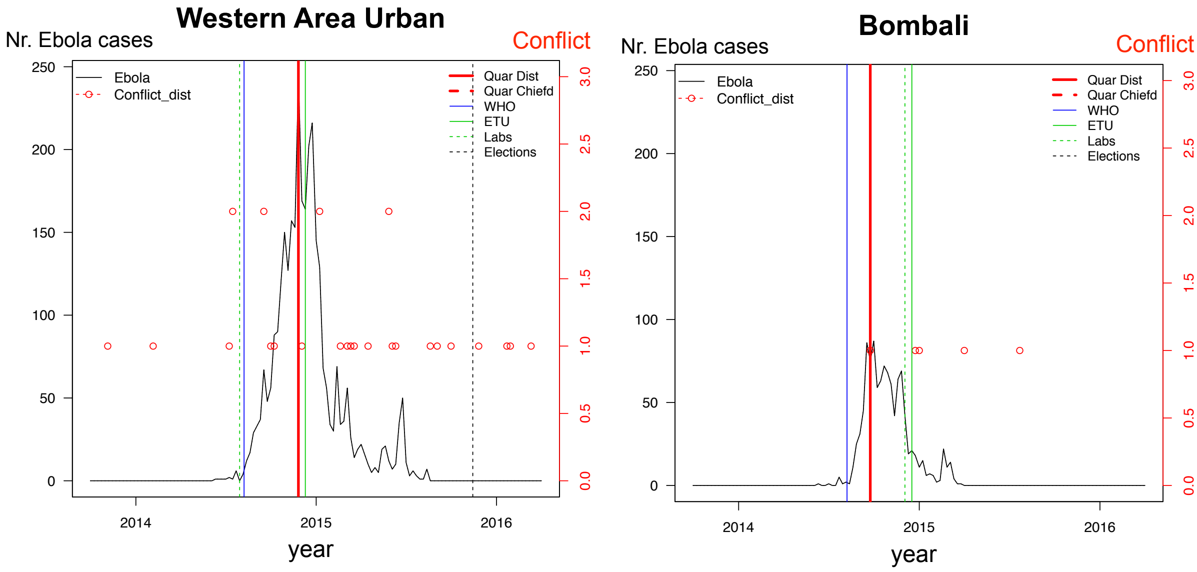
Descriptives

We first give a graphical representation of the data in Figure 2.1. The Figure plots the timeline of conflict events and number of new Ebola infections per week for two highly populated districts in Sierra Leone. The vertical lines show the timing of the WHO intervention and containment efforts. Across districts in our sample we observe a higher frequency of conflict events at times and districts with more Ebola infections. Oftentimes, a conflict event follows an intervention. Figures for all other district are found in Figures D.1-D.4. The geographic spread of conflict is shown graphically in Figures B.1- B.2.

Descriptives for the aggregate number of Ebola cases are shown in Table 2.1. Ebola incidence varied widely across the three most affected countries[38]. The first index case

[38] In this paper we are not able to explain these differences. Population, population density, mobility patterns and distance to the first case are predictors of the spread of Ebola and epidemiologists have shown that the intervention was key in halting the spread of the outbreak. While the emergency assistance was initially led by Medecins Sans Frontieres (MSF) and then coordinated under the auspices of the WHO in

Figure 2.1: Weekly Ebola and Conflict incidence, Sierra Leone



Notes: Weekly timeline of the number of new Ebola infections (left-axis, black line) and of conflict events (right-axis, red dots) for two highly populated districts in Sierra Leone, Western Area Urban (left), and Bombali (right). The vertical lines show the first time the WHO declared Ebola a global health emergency (blue), the imposition of military district or chiefdom quarantines (red), the establishment of Ebola treatment units (ETUs) and of Laboratories (green).

occurred through a contact with an animal reservoir of the Ebola Virus, in Guinea in December 2013. We observe the first cases after January 2014 and in the main descriptive statistics the sample is split into the two years prior to the start of the outbreak and the two years and a half since then, January 2012-May 2016.

Descriptives for the aggregate number of conflicts, namely riots, protests and violence against civilians, are shown in Table 2.2. A simple accounting of conflict incidence in the two years after the start of the outbreak shows a 50% increase in conflict compared to two years prior to the start of the outbreak. This is driven by the countries with highest rates of Ebola cases, namely Liberia and Sierra Leone.

all three countries, there were significant differences in the Ebola response across countries due to distinct national institutions and international donors taking the lead in each response.

Table 2.1: Descriptives - Aggregate Ebola cases

	Number of Ebola cases				
	Confirmed + Probable	Total incl. Suspect	Deaths	Population	Pop./km^2
Guinea	3,814	3,814	2,544	12.3 mn	41
Liberia	5,044	13,416	4,810	4.4 mn	35
Sierra Leone	8,358	11,903	3,956	6.3 mn	79
TOTAL	17,166	29,133	11,310	23 mn	

Notes: Total number of cases: confirmed, probable and suspect cases. In our main analysis we use the sum of confirmed and probable cases, since these have been evaluated by a clinician.
WHO-Definitions: *Suspect case:* (1) any person alive or dead, suffering or having suffered from a sudden onset of high fever and having had contact with a suspect case or a dead or sick animal; or (2) with sudden onset of high fever and at least three Ebola symptoms; or (3) with inexplicable bleeding; or (4) with sudden, inexplicable death. *Probable case:* suspect case that has been evaluated by a clinician or with an epidemiological link with a confirmed case. *Confirmed case:* suspect or probable case with a positive laboratory result.

To illustrate the type of conflict events in our data, we show here one such example:

> "Thousands of protesters marched on the main Ebola hospital in Kenema and threatened to burn it down and remove the patients after a rumour spread about "cannabalistic rituals" occurring there; police fired tear gas to disperse the crowd." Kenema, Sierra Leone, *Reuters*, July 2014

Our outcome variable is the sum of all such events occurring every two weeks in a given chiefdom. A list of examples on Ebola and non-Ebola related civil violence during the Ebola outbreak is reported in Supplementary Appendix Tables D.1-D.2.

Summary statistics to each of our empirical strategies are provided in Tables B.1-B.4.

2.4 Empirical strategy

In this Section we search for a causal relationship between epidemics and conflict, Subsection 2.4.1, precise drivers underlying this effect, Subsection 2.4.2, and impacts of an

Table 2.2: Descriptives - Aggregate Conflict events

	Pre-Ebola 2012-2013	During Ebola 2014-2016/5	During Ebola 2014-15	All 2012-2016/5
Number of Conflicts				
Guinea	89	91	73	180
Liberia	72	168	146	240
Sierra Leone	18	53	43	71
TOTAL	179	313	262	491
Likelihood of Conflict per year per obs. unit (573)				
TOTAL	0.15	0.22	0.23	0.19

Notes: Number of conflict events reported in newspapers throughout a given period in each country. Conflict events are riots, protests and violence against civilians.

epidemic on long-run trust, Subsection 2.4.3. Robustness checks are given in Subsection 2.4.4.

2.4.1 Epidemic spread and civil violence

To identify the effect of Ebola infections on the likelihood of conflict, namely riots, protests and violence against civilians, we use two main sources of variation. The first source of variation comes from the first index case of Ebola, due to the contagion from animal to human being a random and extremely rare event. We exploit this first index case as a random timing event defining our pre-treatment period in a difference-in-difference strategy, as well as geographic variation in total disease incidence, Subsection 2.4.1. The second source of variation comes from the spread of Ebola at high frequency. We exploit the short-run dynamics of the disease to study the impact of new infections on conflict incidence in a panel at high frequency with location, time and region per month fixed effects, Subsection 2.4.1. Alternative specifications and robustness checks are discussed in Subsection 2.4.4.

Difference-in-Differences

In order to study the overall impact of the epidemic on civil violence, we study the change in civil violence after the start of the outbreak, comparing locations hit by Ebola with varying levels of intensity. We do this in a difference-in-difference design with continuous treatment given by the total cumulative number of Ebola cases at the end of the outbreak. The first Ebola case gives us a random timing event defining our pre-treatment period.

$$conflict_{i,\tau} = \beta\ ebolaTotal_i \times PostEpidemic_\tau + \lambda_\tau + \alpha_i + \nu_{i,r,\tau} \tag{2.1}$$

Equation (2.1) describes this first identification strategy. $conflict_{i,\tau}$ is the number of conflicts in one million per capita in location i in yearly quarter τ. The cumulative number of Ebola infections in location i measured at the end of the outbreak is given by $ebolaTotal_i$. $PostEpidemic_\tau$ defines the post-treatment period, taking value 1 at the first quarter of the year 2014 and 0 before that[39]. Standard errors are clustered at the level of a location i, or a group of locations, such as regions or districts r, to allow for serial and spatial dependency[40]. The coefficient of interest is β. It measures the change in conflict incidence after the start of the outbreak for one additional Ebola case in 100'000 per capita.

The identification relies on a parallel trends assumption and the exogenous timing of the event. To allow for the effect to vary over time, we use a more flexible specification than (2.1), using yearly quarter time dummies. This also allows us to provide graphical evidence of parallel trends in conflict incidence for areas with varying levels of Ebola,

[39] The epidemic started at the end of the last quarter of the year 2013. The first index case is believed to be a child infected on December 26, 2013. We take this into account in our flexible estimates specification. The results do not change if we take December 2013 as the start of the outbreak and in fact, given our flexible specification results, this seems to be a more conservative exercise.

[40] The sample analyzed are 507 locations in the 3 most affected countries, Guinea, Liberia and Sierra Leone. In particular, each location refers to chiefdoms in Sierra Leone, sub-prefectures in Guinea and districts in Liberia. A group of locations or region is a larger unit of analysis, namely districts in Sierra Leone, prefectures in Guinea and counties in Liberia.

prior to the start of the outbreak. The specification is shown in equation (2.2).

$$conflict_{i,\tau} = ebolaTotal_i \sum_{\tau=2012:2}^{2016:1} \beta_\tau \; I^\tau + \lambda_\tau + \alpha_i + \nu_{i,r,\tau} \tag{2.2}$$

Compared to the previous equation, we replaced the post-treatment dummy with several time dummies I^τ for each yearly quarter, ranging from 2012 to 2016, with the first quarter of 2012 as omitted category. The coefficient β_τ gives us the difference in conflict incidence at each quarter of a year due to one additional Ebola case in 100'000 per capita.

A potential concern is the possibility that post-treatment selection into high Ebola incidence is driven by factors that also change conflict incidence over time. Most of the changes occurring in the months after the first index case are driven by the epidemic and we interpret them as channels underling the impact of an epidemic on civil violence. For instance, an unequal distribution of new health centers or military aid can affect both Ebola incidence and conflict events. This is one of the main channels we stress in this paper driving the impact of an epidemic on civil violence. To address the possibility of time-varying conditions affecting both the spread of Ebola and conflict incidence, such as movement of police forces unrelated to the epidemic, we instrument the end-level of Ebola in each location with the geographic distance to the first index case, also known as epicenter. In particular we use the linear and quadratic geographic distance interacted with the post-treatment dummy and an indicator variable for each country, to allow for non-linear effects in distance and heterogeneity across countries[41]. Geographic distance

[41] We add the first stage shown in equation (2.3) to our equation (2.1) above.

$$\begin{aligned} ebolaTotal_i \times PostEpidemic_\tau = & \sum_{c=Country} \gamma^c \times I(c) \times DistEpicenter_i \times PostEpidemic_\tau \\ & + \sum_{c=Country} \gamma^c \times I(c) \times DistEpicenter_i^2 \times PostEpidemic_\tau + \lambda_\tau + \alpha_i + \nu_{i,r,\tau} \end{aligned} \tag{2.3}$$

Where $DistEpicenter_i, DistEpicenter_i^2$ are the linear and quadratic geographic distance to the epicenter. Note that there are only three countries. The quadratic term allows for non-linear effects in distance and provides a more flexible specification. The indicator variable for each country, $I(c)$, allows the effect to vary for each country. Other specifications, such as using only the linear distance interacted with each country and the capital lead to similar predictions. Using the simple distance is not predictive of the total cumulative number of Ebola cases, which suggests that there are non-linear effects in distance and heterogeneity across countries.

measures to the first index case are a predictor of the total cumulative number of Ebola infections and it is used in other contexts to study impacts of epidemics, such as Oster (2005) for the HIV/AIDS epidemic. The exclusion restriction is that time-varying unobservables arising after the start of the outbreak are not driven by the distance to the epicenter. We show that the incidence of conflict prior to the start of the outbreak is uncorrelated with distance to the epicenter, Table B.6. Expected correlates of civil violence that appear statistically associated with the distance to the epicenter are added as controls, interacted with the post-treatment dummies.

Results on the impact of the epidemic over yearly quarters

Descriptive statistics in yearly quarters are shown in Table B.1. The difference-in-difference results are shown in Table 2.3 for all countries. Columns (1) and (2) show no differential trend in conflict incidence prior to the start of the outbreak in areas with higher Ebola incidence in comparison to areas with lower incidence.

The difference-in-difference results are reported in Columns (3)-(5). They indicate that one additional Ebola case in 100'000 per capita increases the likelihood of civil violence by $0.006 - 0.01$ or by $0.8 - 1.3\%$ from a baseline mean (standard deviation) incidence of conflict in one million per capita of 0.76 (8.64) over a quarter of a year. With a mean incidence of 50 Ebola cases in 100'000 per capita this means that a location moving from no cases to the average level of infections increases the likelihood of conflict by $40 - 66\%$ or by $0.3 - 0.5$ additional conflict events in one million people per capita within three months. In some locations the Ebola incidence was as high as 2105 in 100'000 per capita. The 2SLS results are similar in magnitude compared to the OLS results. The slightly larger coefficient is plausibly due to measurement error in the number of infections[42]. The first stage is shown in Table B.5. Areas that are closer to the epicenter have higher Ebola incidence, but there is a non-linear effect in distance. Adding pre-determined covariates

[42] We have patient records for Sierra Leone and Guinea, but for Liberia our measure is from the WHO website and it is aggregated at county level. There was a large number of suspect cases in Liberia that have not been classified yet.

Table 2.3: Difference in Differences relative to the first index case in West Africa

Outcome: conflict(quarter)	Pre-Ebola		Pre/Post Ebola			
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
ebolaTot × Trend	0.0001	-0.0001				
	(0.0001)	(0.0002)				
ebolaTot × PostEbola			0.0055***	0.0089**	0.0100**	0.0092*
			(0.0017)	(0.0036)	(0.0040)	(0.0043)
N	4672	4672	10512	10512	3870	3870
Time FE	Y	Y	Y	Y	Y	Y
Chiefd FE	Y	Y	Y	Y	Y	Y
Controls					Restr.	Y

(Clustered SE) by Dist; Controls Restr.: sample restricted to locations with household survey data.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

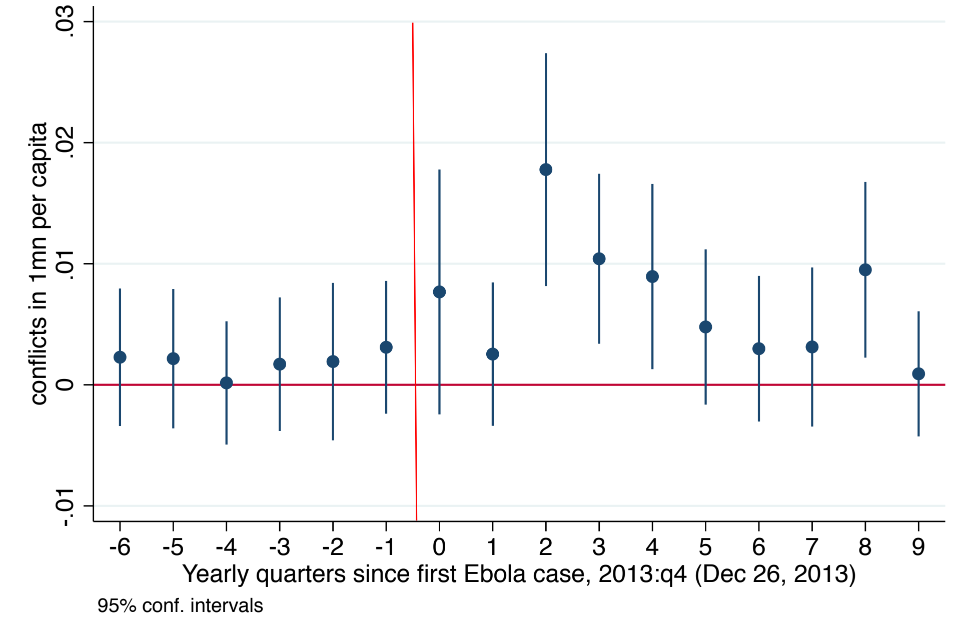
Notes: $conflict$ is the number of conflicts in each yearly quarter in 1 million per capita. $ebolaTotal$ is the total cumulative number of Ebola cases measured at the end of the outbreak for each location in 100'000 per capita. $PostEbola$ is a post-treatment dummy taking value 1 from 2014 on, after the first Ebola case is observed.
2SLS results use the geographic linear and square distance to the first index case as instrument for the total cumulative number of Ebola infections. First stage F-Statistic: 10.24, Table B.5.
Controls: Traditional religion, trust in leaders and votes or preferences for the incumbent measured pre-epidemic and interacted with the post-treatment dummy. The choice of these controls is based on the fact that they are correlated with the geographic linear and square distance to the epidemic, potentially affecting the likelihood of conflict, Table B.6.

expected to be correlates of civil violence, interacted with the post-treatment dummy does not change our coefficient, compared to the sample restricted to locations with household survey data used to construct those covariates[43]. Our preferred specification is the simple OLS, given that both strategies lead to similar results, that we observe parallel trends in conflict incidence prior to the outbreak and that most unobservables are interpreted as mechanisms driving civil violence in the context of the epidemic.

The difference-in-difference design with flexible time coefficients is shown graphically in Figure 2.2 for all countries and Figure 2.3 for Sierra Leone. The Appendix Figures B.8-B.5 summarize results for Liberia and Guinea. We find evidence of parallel trends in conflict incidence prior to the start of the outbreak and a spike immediately following

[43]Controls: Traditional religion, trust in leaders and votes or preferences for the incumbent measured pre-epidemic and interacted with the post-treatment dummy. The choice of these controls is based on the fact that they are correlated with the geographic linear and square distance to the epidemic, potentially affecting the likelihood of conflict, Table B.6.

Figure 2.2: Difference in Difference relative to first case in West Africa - All countries



Notes: Coefficients on the total end-number of Ebola cases in one location × dummy for a yearly quarter. Calendar time since first case. Omitted category: 2012:q1.

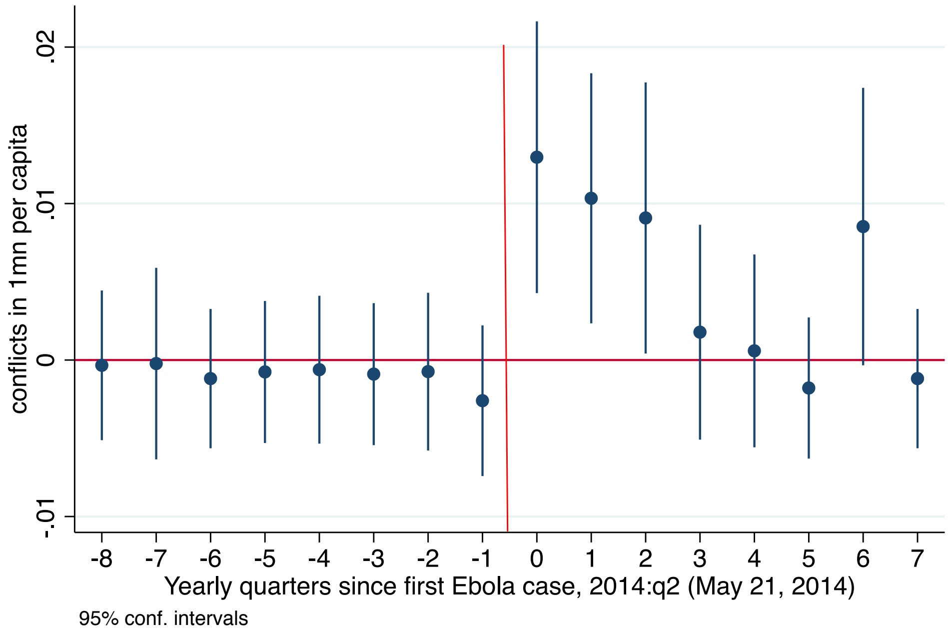
the first cases arriving in Liberia, March 2014, and Sierra Leone, May 2014. This does not hold overall for Guinea, which had a much smaller infection rate as percentage of the population. However, a similar pattern arises for Guinea when we use the arrival of the epidemic in each prefecture as a reference point to study its impact on each sub-prefecture, Figure B.6[44]. The effects for each country indicate an increase in conflict incidence ranging from $0.01 - 0.04$ or $1.3 - 5.2\%$ from a baseline mean incidence of conflict in one million per capita of 0.76 per quarter of a year, with the larger effect representing Liberia[45]. We see the largest impacts during the last three quarters of 2014, namely throughout the core of the outbreak. The effects fade over time, indicating potential non-linearities or a change as the state response evolves over time. We can think of periods 0-2 in Figure 2.2 as pre-intervention periods. Strictly speaking, the pre-intervention period corresponds to periods 0-1 only, before the epidemic is officially declared in Guinea in March, 2014 following a laboratory test in Lyon, France, that confirmed the Ebola virus. However, MSF

[44]We do the same for Sierra Leone, using the first arrival of the epidemic in a district to study its impact on each chiefdom, Figure B.7; but not for Liberia, since we do not have Ebola data at lower than county level.

[45]See interpretation in the paragraph above.

was quickly overwhelmed and the states had little capacity to respond to the outbreak until the international aid package started arriving in August 2014, namely period 3. We observe the first military district-quarantines in that month too.

Figure 2.3: Difference in Difference relative to first case in country - Sierra Leone



Notes: Coefficients on the total end-number of Ebola cases in one location (chiefdom) × dummy for a yearly quarter. Calendar time since first case in Sierra Leone. Omitted category: 2012:q1.

High frequency Panel data

Next we exploit the short-run dynamics of the disease to study the impact of new infections on civil violence at high frequency. The main panel data specification is summarized in equation (2.4).

$$conflict_{i,t} = \beta \; ebola_{i,t-1} + \mathbf{X}_{i,t-1}\Gamma + \alpha_i + \lambda_t + \mu_{r,\tau} + \epsilon_{i,r,t} \qquad (2.4)$$

The time dimension is at two-week level t. We aggregate our weekly data at that level to reduce possible measurement error in the number of infections due to the improvement of medical and testing conditions changing over time. We choose two weeks because

Ebola symptoms arise on average within 8-12 days after infection with the virus. In this specification $conflict_{i,t}$ is the number of conflicts in one million per capita in location i in a two-week period t. $ebola_{i,t-1}$ is the number of new Ebola infections in location i in period $t-1$. In our main specification we do not add any covariates. We will consider basic covariates $\mathbf{X}_{i,t-1}$, namely past infections, cumulative infections and past conflict incidence, for robustness. Our specification conditions on location α_i, time λ_t and month$\times$region fixed effects[46] $\mu_{r,\tau}$. Standard errors are clustered at the level of a group of locations r, to allow for serial and spatial dependency[47]. The coefficient of interest is β. It measures the change in conflict incidence in the next two weeks for one additional Ebola case in 100'000 per capita in the past two weeks.

Our main identification strategy is a simple OLS. We rely on the spread of new Ebola infections in the past two weeks being exogenous at two-week level, conditional on location, time, region$\times$month fixed effects, and possibly other time-varying covariates[48]. Most time-varying confounders we can think of are related to the epidemic and are interpreted as channels. For instance, if the imposition of safe burial practices in areas with more Ebola incidence leads to significant opposition against preventive measures, this could generate new infections in the future and drive conflict incidence. In fact this paper suggests that a state response with little sensitivity to local customs is an important reason explaining why Ebola drives subversive violence.

We discuss a number of alternative strategies in Subsection 2.4.4 on Robustness checks. In particular we use two instrumental variables strategies to strengthen our identification. First, we instrument the number of new infections in a given location by the turning on and off of the epidemic in neighboring locations, to ensure that our findings are not driven by time-varying confounders with persistent effects in a given location. Second, we construct a predicted Ebola measure from the medical literature that relies on the geographic

[46] Note that region is necessarily at a higher level of aggregation than our location. Instead of month we will consider three time periods, corresponding to six weeks.

[47] When we look at each country separately or when we condition our sample to regions for which we have household survey data, we cluster at location level instead, in order to avoid having too few clusters

[48] OLS identifying assumption: $E(\epsilon_{t,i}|ebola_{i,t-j}, X_{i,t-j}, \alpha_i, \lambda_t, \mu_{r,\tau}) = 0$ for all j.

position of each location, infections several periods in the past and fixed characteristics, with the aim to address the possibility of non-standard measurement error in infections. We also estimate the model by Generalized Method of Moments (GMM), allowing for dynamic effects. The results are similar across specifications and our preferred specification is the simple OLS.

We next motivate the particular the choice of $ebola_{i,t-1}$ at time $t-1$ as our measure of interest. In theory new infections could cause distress in any future time period. We conjecture that Ebola has an impact in matter of few weeks, since people die or recover within four weeks after infection, that is, within two weeks after symptom onset. However, we can answer this question empirically. We estimate the equation above (2.4) several times for conflict incidence in different time periods in the future, conditional on Ebola and conflict incidence in the past. The logic follows that of a local linear projection proposed by Jordà (2005)[49]. The strategy is summarized in equation (2.5).

$$conflict_{i,t+h} = \beta_h \; ebola_{i,t} + \sum_{j=1}^{J} \gamma_j \; ebola_{i,t-j} + \sum_{j=1}^{J} \rho_j \; conflict_{i,t-j} + \alpha_i + \lambda_t + \epsilon_{i,r,t} \quad (2.5)$$

for $h \in [0, H]$.

The coefficient of interest β_h measures the impact of new infections on civil violence h periods from now, net of other things affecting Ebola or conflict incidence in the past $J = 9$ periods. We plot β_h for each time horizon $h \in [0, 10]$[50]. These plots give us an impulse response function indicating that new infections in 100'000 per capita impact the likelihood of civil violence only in the next period. This provides an empirical justification to our main specification (2.4).

[49] This is similar to controlling for different lags in infections, but provides a more complete analysis of the impact of Ebola infections on conflict incidence. We also show results for our baseline specification (2.4) and controlling for several lags in Ebola, discussed under robustness checks.

[50] We choose $H = 10$ future time periods and $J = 9$ lags and the results are robust to different choices of H, J

Results on the impact of the epidemic at high frequency

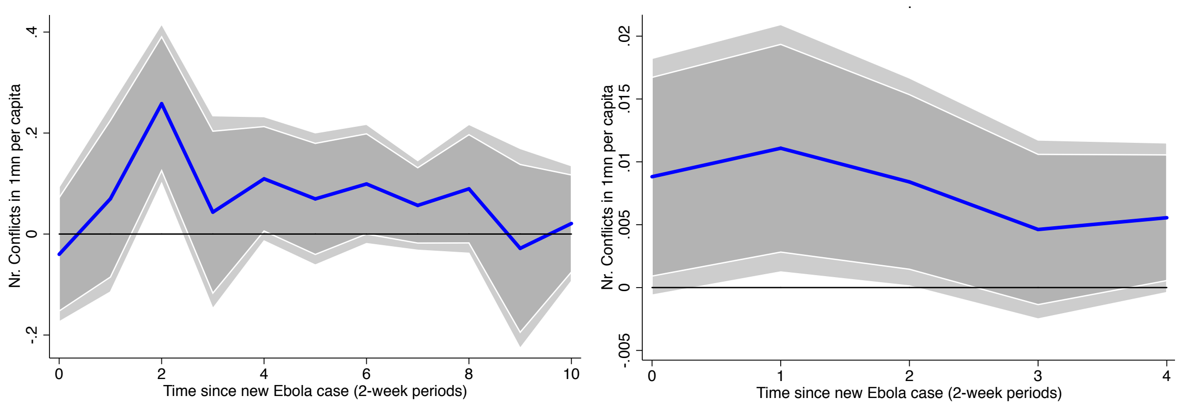
Descriptive statistics for our panel specification are shown in Table B.2.We first give a graphical representation of impulse responses for the extensive margin and intensive margins. The extensive margin tells us whether the presence of the epidemic, $ebola \in \{0, 1\}$, has an impact on civil conflict, Figure 2.4, left-hand-side. The impacts are concentrated in the two periods after new infections emerge. Locations hit by the epidemic have on average 0.26 more conflict in one million per capita in the following four weeks compared to locations not hit by the epidemic in that time period. The intensive margin is the impact of new Ebola infections in 100'000 per capita on conflict incidence, Figure 2.4[51], right-hand-side. The effect is statistically significantly different from zero one period after new infections hit a given location, motivating our specification (2.4). The figure shows that one new case in 100'000 per capita increases the likelihood of conflict incidence by 0.01 from a baseline mean incidence of 0.117 pre-epidemic or 0.128 for the whole period, thus a $7.8 - 10\%$ increase in the likelihood of conflict incidence in one million per capita. There is suggestive evidence of persistence, but the long-run effects are not statistically significant.

The main results on the impact of new infections on conflict incidence are summarized in Table 2.4, which includes several specifications discussed in detail Subsection 2.4.4 under Robustness checks. The epidemic generates a large short-run immediate effect on increasing the likelihood of conflict. Conflict in one million per capita in the next two week rises by $0.012 - 0.013$ in a given location as a consequence of one new infected person in that location[52]. This supposes a $9 - 10\%$ change in the incidence of conflict for one additional Ebola infection in 100'000 per capita, from a baseline incidence of 0.117 pre-epidemic or 0.128 for the whole period. The results are therefore identical to the local projections in which we control for 9 lags in Ebola and conflict. The average number of

[51]We show the effects for the 10 future periods in the Appendix, Figure B.9

[52]Ebola is measured at county, chiefdom and sub-prefecture level and conflict is measured at district, chiefdom and sub-prefecture level, for Liberia, Sierra Leone and Guinea, respectively. All regressions are population-weighted.

Figure 2.4: Impulse response for the presence of the epidemic, or extensive margin (LHS), and for the number of Ebola infections (RHS), on conflict incidence.



LHS graph: Impulse response for the presence of the epidemic, or extensive margin, on conflict incidence for 10 future time periods. The coefficients of $ebola_{t-1} \in \{0, 1\}$ in equation (2.5) are plotted, with 90% and 95% confidence intervals. We condition on 9 lags in ebola and conflict (two-week frequency).
RHS graph: Impulse response for local projections for the impacts of ebola infections in 100'000 per capita (intensive margin) on conflict incidence for 4 future time periods. The coefficients of $ebola_{t-1}$ in equation (2.5) are plotted, with 90% and 95% confidence intervals. We condition on 9 lags in ebola and conflict (two-week frequency). The effects for the 10 future periods are shown in Figure B.9.

Ebola infections for locations that were already hit by the epidemic in 2014 is 8 cases in 100'000 per capita in a two-week period. The maximum is 500 cases. These estimates mean that moving from no cases to the average level of Ebola during the first year of the outbreak increases the likelihood of civil violence by 0.112 within the next two weeks, thus doubling the mean incidence of conflict in a matter of weeks. We find only a suggestive impact of cumulative Ebola cases, much smaller in magnitude and less precisely estimated than the impact of new infections, Table B.8. This provides further evidence that the main effects are immediate. The results are robust to different specifications. Robustness checks and details on all specifications are discussed in detail in Subsection 2.4.4.

Table 2.4: High-frequency panel: Summary of Results for All countries

Outcome: conflict(t)	All countries					
	(1) OLS	(2) OLS	(3) OLS	(4) GMM	(5) IV-eb(t-2)	(6) IV-ebOthers(t-2)
ebola(t-1)	0.0138***	0.0146***	0.0123**	0.00756**	0.0162***	0.0238***
	(0.0039)	(0.0041)	(0.0049)	(0.0036)	(0.0047)	(0.0076)
conflictOthers(t-2)						0.0971
						(0.0754)
N	66576	66574	65990	66576	65404	61320
R2	0.125	0.143	0.144		0.145	0.130
Time FE	Y	Y	Y		Y	Y
Chiefd FE	Y	Y	Y		Y	Y
Reg × Month FE		Y	Y		Y	
Clusters	Dist	Dist	Dist		Dist	Dist
Controls						
ebolaCum			Y		Y	
ebola(t-2)			Y			

(Robust SE)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of Ebola infections over time. Column (4) estimates a dynamic panel of conflict on past Ebola using all possible lags as GMM-type instruments for the difference equation. Column (5) uses only $ebola(t-2)$ as instrument for $ebola(t-1)$. Column (6) uses the presence of the epidemic in neighboring locations in periods $\{t-2, t-3, ..., t-10\}$ interacted with country, capital and district-capital as instruments for $ebola(t-2)$. Results using only $\{t-2\}$ as instrument are shown in the Appendix, Table B.11. $conflictOthers(t-2) \in \{0,1\}$ is the presence of conflict in the region except the own. First stage: $R^2 = 0.21$, $F - Statistic = 84.12$.

2.4.2 Drivers of civil violence

Once we have established that the epidemic leads to civil violence, in the previous Subsection, we now test our hypotheses on precise channels underlying this effect.

Epidemics affect the relationship between citizens or between citizens and the state. They change citizens' perception of the state and demands from it in at least three ways. First, they move the state to adopt coercive measures, in order to halt contagion. This supposes an immediate threat to citizens, which leads to social unrest. If this coercion is regarded as illegitimate, or excessive, it can increase the benefits from a riot aiming at countering these measures. Second, they generate a demand for public goods, as people need health treatment. This lowers the opportunity cost of engaging in violence, or creates a benefit of doing so if this eventually led to the establishment of treatment centers. Third, they require a change in cultural practices, such as burial practices, which are induced by state authorities. Changing them is more costly for people with strong religious beliefs and the potential benefits of adopting new cultural practices are less clear if there is low trust in institutional authorities. We hypothesize that these changes are important drivers of subversive violence in the context of an epidemic. Epidemics also tear families apart and affect the relationship between citizens, fearing contagion. In this paper we highlight the importance of institutional channels, those that are influenced by policy makers, through the choice of a particular emergency response.

To study these potential channels we first look at the main patterns in our data. What type of conflict was affected by the epidemic, who were the actors involved? We then study how the shock propagates over time and space. We also analyze whether the impacts vary over different time periods corresponding to distinct intervention phases and by country. We interpret results from these exercises as suggestive. Secondly, we study the impact of the state response and emergency assistance that followed. Finally, we study the role of trust and religious beliefs as determinants of civil violence in the context of an epidemic.

Main patterns

We start from the observation that the Ebola outbreak was associated with a particular kind of conflict, namely subversive violence, such as riots, protests and violence against institutional authorities. Tables 2.5-2.6 suggest that most conflict events are violent, but also non-violent protests arise, they are directly related to the epidemic outbreak and they involve either civil actors or both civil and state actors, in line with medical records and anthropologists accounts of violence emerging as a consequence both of social unrest and the state response to it.

Table 2.5: Types of Conflict

	(1) conflict	(2) Viol.a.Civ.	(3) Riots	(4) Protests	(5) Riots/Protests	(6) Viol.	(7) Non-Viol.	(8) EVD/Health	(9) Non-EVD
ebolat-1	0.0146***	0.00101	0.00828**	0.00518***	0.0135***	0.00915**	0.00550***	0.0118***	0.00283
	(0.00415)	(0.001000)	(0.00366)	(0.00179)	(0.00419)	(0.00370)	(0.00189)	(0.00441)	(0.00196)
Observations	66574	66574	66574	66574	66574	66574	66574	66574	66574
R^2	0.143	0.035	0.090	0.081	0.131	0.096	0.087	0.054	0.140

(Clustered SE) by Dist, with 2week FE, Chiefd FE, 3week x Reg FE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. *ebola* is the number Ebola cases in 100'000 per capita. We measure different types of conflict events: violence against civilians, riots, protests, riots and protests, violent conflict, non-violent conflict, Ebola or Health-related conflict, Non-Ebola related conflict.

Table 2.6: Actors in Conflict

	(1) conflict(t)	(2) State	(3) Civilians	(4) State/Civil	(5) CivilOnly	(6) StateOnly
ebola(t-1)	0.0146***	0.00838**	0.0131***	0.00837**	0.00473***	0.0000164
	(0.0041)	(0.00398)	(0.00458)	(0.00398)	(0.00151)	(0.000217)
Observations	66574	66574	66574	66574	66574	66574
R^2	0.143	0.089	0.104	0.084	0.053	0.028

(Clustered SE) by Dist, with Time FE, Chiefd FE, Month x Reg FE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. *ebola* is the number Ebola cases in 100'000 per capita. A given conflict can have one or several types of actors. At least a state actor, at least civilians, both the state and civilians are involved, only civilians or only state actors are involved.

The impact of an epidemic on violence is very localized, as shown in Table B.18, and spillovers from neighboring areas are not significantly different from zero, which is in line with the geography of the countries, in which chiefdoms, sub-prefectures and counties or districts are relatively far from each other[53].

We study how the shock evolves over time, according to the different intervention phases. This is shown in Table 2.7. The results show that the epidemic generates violence in all phases, pre and post-intervention. They provide suggestive evidence of these being largest in August and September 2014, which are the most convulsive months as emergency assistance arrives and a major state response is set in place. The difference is not significantly different from the main effect, when comparing each period separately, column (3). In search for a structural break we study whether the effect changes in August, September or October, columns (4)-(6). We find that the impact of a new Ebola case on conflict incidence is significantly reduced in the post-October period, compared to the period before. This shows that the epidemic generated civil violence at early stages, when the epidemic was unknown, prior to the huge influx of emergency assistance, column (4). It also provides suggestive evidence in favor of numerous accounts by anthropologists and people involved in the Ebola response, that as the state response evolved, taking into account local customs, social unrest was diminished, column (6). A competing explanation is that social unrest subsides after the peak of the epidemic outbreak is reached. In Table B.19 we provide evidence against this competing explanation. The structural break is not driven by the peak of the epidemic, defined as the period in which a region hits the maximum of Ebola cases, column (6). The shock does fade over time column (7). This is consistent with both the state response adapting to people's culture and people's beliefs and customs evolving, a channel shown in Chapter 3 using exogenous variation in exposure to radio campaigns. There are some non-linearities, but they are of small magnitude, for instance including a square term or studying the impact of cumulative number of Ebola cases, Table B.20. In fact, whether there is any Ebola case in a given

[53]Corresponding to our measures of location for Sierra Leone, Guinea and Liberia, respectively

Table 2.7: Conflict throughout the outbreak

Outcome: conflict(t)	No omitted cat.		Vs Before			
	(1)	(2)	(3)	(4)	(5)	(6)
ebola(t)	0.0137***		0.0135**	0.0104**	0.0182**	0.0205***
	(0.0043)		(0.0058)	(0.0049)	(0.0071)	(0.0067)
ebola(t) × preJuly2014		0.0135**				
		(0.0058)				
ebola(t) × Aug2014		0.0274**	0.0139			
		(0.0135)	(0.0136)			
ebola(t) × Sep2014		0.0203**	0.00675			
		(0.0091)	(0.0109)			
ebola(t) × postOct2014		0.00594**	-0.00759			-0.0146**
		(0.0025)	(0.0059)			(0.0062)
ebola(t) × postAug2014				0.00380		
				(0.0067)		
ebola(t) × postSep2014					-0.00610	
					(0.0085)	
Mean	0.187	0.187	0.187	0.187	0.187	0.187
N	66576	66576	66576	66576	66576	66576
R2	0.142	0.142	0.142	0.142	0.142	0.142

(Clustered SE) by Dist; Time, Chiefd, Reg × Month FE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The period before the huge emergency assistance package corresponds to pre-July 2014. Our prior is that August and September 2014 are the most convulsive months as emergency assistance arrives and a major state response is set in place. This response evolves in the months following October 2014. The epidemic peaks in September in Liberia, in November in Sierra Leone and in December in 2014.

region, generates a lot of distress, Table B.19, column (5).

The epidemic generates different effects for each country. The impacts are largest for Sierra Leone and a bit smaller for Liberia, in both cases statistically significant, Table B.21. For Guinea the mean effect is small and not statistically significant, as in our difference-in-difference estimates. Guinea is also the country with least number of cases and fatalities and the role of information campaigns in halting social unrest and the spread of Ebola is studied in Chapter 3.

State response

We now study the role of the state response, or emergency assistance, in fueling social unrest. In particular we test whether perceived state coercion and demand for public goods are drivers of civil conflict and study the effect of military district quarantines and the establishment of health treatment centers on conflict incidence. This has direct policy relevance, since they depend on the particular type of emergency assistance that is provided.

Epidemics change the relationship between citizens and the state and the particular state response can in principle dampen or fuel social unrest. Halting the outbreak requires treating patients and preventing further contagion. Some of the measures adopted by the state are coercive, they can are misunderstood, considered illegitimate, or in the context of weak state capacity, they are insufficient, such as limited amount of health facilities.

Perceived state coercion, such as military presence, can lower the probability of success of a mob, discouraging it in the first place. This is a similar argument to the role of military and police resources discouraging insurgency in Fearon and Laitin (2003). However, the role of state coercion in this context can potentially further undermine the state, rather than strengthening it. Quarantines are in general a form of coercion, which could have public benefits[54], but they have private costs. People that are not infected or whose infectiousness is not confirmed with a laboratory result have restricted movement and are often exposed to other infected people. Military district quarantines are an extreme form of state coercion in the context of an epidemic (Moon, 2015; Richards, 2016; Hofman and Au, 2017). With low trust in authorities, this can impact the spread of rumors and low uptake of other protective measures, such as resistance against the imposition of safe burial practices or contact tracing, isolation and patient care.

This means that the opening health treatment centers could lead to a rise in social unrest,

[54] Whether they are optimal depends on the type of quarantine and on the citizens response to it. If they lead to civil violence and low health uptake, they can be very counterproductive (Moon, 2015; Richards, 2016; Hofman and Au, 2017).

due to this previous experience with the state. This is especially the case if people are uninformed about the benefits of treatment centers or if they are in fact very low because there is under-capacity or soaring death rates. The opening of treatment centers should lead to a rise in civil violence in that case. However, the epidemic generates an exogenous demand in public goods, due to the need for health treatment. We should expect a drop after the establishment of treatment centers, if people trust the state, they are informed about the benefits of treatment centers and there is enough access to them. In that case, we should see a drop in riots. This depends in principle on how the state response is perceived, which relies on previous experience with the state. Finally, this can have long-term effects on trust, further undermining weak states.

Empirical strategies to disentangle these channels are discussed next. Descriptive statistics for the state responses we observe are shown in Tables B.3-B.4.

State coercion

To study the role of perceived state coercion as a driver of civil violence we measure the impact of military district-quarantines on civil violence. Our empirical strategies are in the spirit of a difference-in-difference design. First, we look at the change in conflict after a quarantine, comparing locations that have one to those that do not. We restrict the sample to locations that have sufficient level of Ebola incidence, to have comparable locations. Secondly, we look at the conflict incidence during the time of a quarantine in a standard panel specification with location and time fixed effects. Thirdly, we restrict the sample to ever-quarantined districts and compare the incidence in conflict at different points in time for these districts. Finally, we corroborate our results with graphical evidence in an event study design. The main strategy is summarized in equation 2.6.

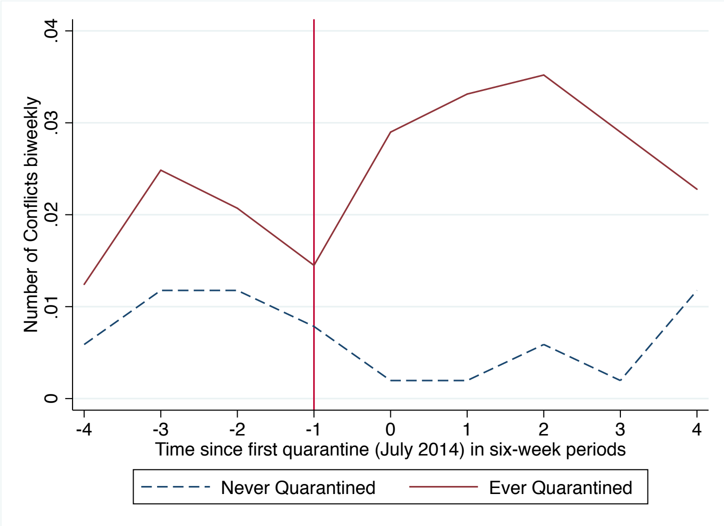
$$conflicts_{i,t} = \gamma_0 PostQuar_{i,t} \times EverQuar_i + \mathbf{X}_{i,t}\Gamma + \alpha_i + \lambda_t + \epsilon_{i,t} \tag{2.6}$$

The treatment dummy $EverQuar_i$ indicates whether a location i has ever been quarantined. $PostQuar_{i,t}$ is a treatment dummy that takes value 1 if a location i has already been quarantined and 0 otherwise. Note that $EverQuar_i$ is redundant, we add it here for clarification. Only time-varying factors or only location-varying factors are captured by the fixed effects. γ_0 gives us the change in conflict incidence for quarantined locations after they are quarantined, compared to non-quarantined locations. Alternatively we will replace this by a dummy $WithinQuar_{i,t}$ that takes value 1 only if the location i is in a quarantine in at time t. In that case the γ_0 measures the change in conflict incidence for quarantined locations during the quarantine, compared to other periods without the quarantine. We run the simple specification without covariates and then include Ebola as covariate to ensure that the results are not driven by the spread of Ebola.

Identification relies on parallel trends and the assumption that quarantines are set up by the state to stop the epidemic outbreak, not to solve conflict incidence. We provide evidence of no trend differential for quarantined locations prior to the establishment of the quarantine, compared to other locations, Figure 2.5. Additional graphical evidence for parallel trends and immediate impacts of the quarantine in several event studies using either calendar time since first quarantine or actual time that a location is quarantined are shown in Figures 2.5-B.15. Table B.22 shows that quarantines are established in locations based on potential disease spread, such as distance to the epicenter, and access to roads. There is no evidence of strategic placement of quarantines to hurt opposition members or other strategic motives, Table B.23. However, they are placed in locations with low trust in the army, in leaders and in local institutions, hence potentially further exacerbating trust in the long-run.

The main results are summarized in Table 2.8. We restricted the sample to locations that have at least 20 cumulative cases of Ebola in order to have comparable units. There is no significant trend difference prior to the establishment of a quarantine, even after controlling for prior Ebola cases, columns (1)-(2). While more conflictual locations are more likely to have a quarantine, there are parallel trends in conflict incidence prior to

Figure 2.5: Parallel trends in Quarantined vs. Non-Quarantined locations



Notes: Conflict incidence for ever-quarantined and never-quarantined locations.

their establishment and we see a rise in conflict incidence thereafter. The results indicate a huge rise in civil violence in weeks in which area blockades are in place, compared to other weeks, columns (3)-(4). We see the same effect when looking at the change in conflict incidence for the whole period after the establishment of a quarantine, columns (5)-(6). The point estimates indicate that having a quarantine in place means $0.3 - 0.5$ higher conflict incidence than not having it. This effect is $1.5 - 2.5$ times larger than the effect of being hit by the epidemic in a given week, column (5) in Table B.19. The results also indicate that the impact of new Ebola infections is stable and statistically significant. We provide results restricted to locations that were ever quarantined in Table B.24. The results are identical. Graphical evidence is provided in Figure B.12. It shows the change in conflict incidence over time due to an additional quarantine in 100'000 per capita. We see a spike in conflict during the six weeks following the first time quarantines were imposed, in June/July 2014. Similar strategies using the time of the quarantine in each location show similar results. They are shown in Figures B.13-B.14, conditioning on having at least 5 and 10 cumulative Ebola cases. We interpret these results indicating that perceived state coercion generates social unrest, with potential impacts on health uptake of other measures. They show that the immediate threat of state coercion is stronger

Table 2.8: Military district-quarantines - OLS results (including all locations)

Outcome: conflict(t)	Pre-Quar		Pre/Post-Quar			
	(1)	(2)	(3)	(4)	(5)	(6)
WithinQuar			0.296*	0.468**		
			(0.1540)	(0.1784)		
PostQuar					0.371*	0.508**
					(0.1992)	(0.2227)
PostQuar × Trend	0.00473	0.00595*				
	(0.0028)	(0.0030)				
EverQuar × Trend	-0.000642	0.0127				
	(0.0046)	(0.0247)				
ebola(t-1)		0.00828***		0.00755**		0.00806***
		(0.0027)		(0.0029)		(0.0026)
ebolaCum(t-2)		-0.00143**		-0.00162**		-0.00140**
		(0.0006)		(0.0006)		(0.0006)
N	2218	2000	2218	2000	2218	2000
R2	0.288	0.313	0.287	0.311	0.288	0.312
Time FE	Y	Y	Y	Y	Y	Y
Chiefd FE	Y	Y	Y	Y	Y	Y
cumEbola> 20	Y	Y	Y	Y	Y	Y

(Clustered SE) by Dist

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. *ebola* is the number Ebola cases in 100'000 per capita. *ebolaCum* is the cumulative number of cases in 100'000 per capita. $WithinQuar$ is a dummy variable taking value 1 if the location is currently under a military quarantine and 0 otherwise. $PostQuar$ takes value 1 if the location has already been quarantined once and 0 otherwise. $EverQuar$ takes value 1 if the location will ever be quarantined and 0 otherwise.

than its potential benefit from discouraging civil violence.

Public goods

To learn about the role of the demand for public goods as a driver of conflict, we measure the impact of the epidemic on conflict incidence for varying access to Ebola treatment units (ETUs), community care centers (CCCs) and laboratories. Ebola patients were treated in Ebola treatment units (ETUs), which were established first by MSF and then under the auspices of the WHO and created ad-hoc for treatment purposes. Laboratories were set in place for rapid testing of the virus and their establishment rapidly increased with the influx of emergency assistance. They were also decided at national and international level. Community care centers were local hospitals that turned into transit centers for first care of Ebola patients. They were opened spontaneously by local communities, as opposed to Ebola treatment units and laboratories. We therefore see an opportunity to study the implementation of ETUs and laboratories as a shock to study its impact on civil violence. On the other hand, we will also ask whether conflict incidence throughout the epidemic predicts the amount of CCCs that opened. Since this last exercise is not causal we interpret the results as suggestive.

The role of demand for public goods is measured as a heterogeneous treatment effect of new Ebola cases on conflict incidence. The main specification is summarized in equation (2.7)

$$\begin{aligned} conflict_{i,t} = {} & \beta_0 \; ebola_{i,t-1} + \beta_1 \; ebola_{i,t-1} \times PostEmergency_t \\ & + \gamma_0 \; NearETU_i^{end} \times PostEmergency_t \\ & + \gamma_1 \; ebola_{i,t-1} \times NearETU_i^{end} + \gamma_2 \; ebola_{i,t-1} \times NearETU_i^{end} \times PostEmergency_t \\ & + \mathbf{X}_{i,t}\Gamma + \alpha_i + \lambda_t + \epsilon_{i,t} \end{aligned} \tag{2.7}$$

Table B.22 shows that public goods are established in locations based on potential disease spread, such as distance to the epicenter, population density and access to roads. CCCs are established in locations with prior access to health centers, mechanically. There is no evidence of strategic placement of public goods to benefit members of the incumbent group, Table B.23.

Identification relies on the fact that treatment centers were new, established ad-hoc to counter the spread of Ebola and decided externally by international organizations, with their greatest availability following the influx of money nine months after the start of the outbreak, when the international community realized the epidemic was a global health concern. The decision of the international community to intervene serves as a timing event that is exogenous with respect to the local spread of Ebola and conflict incidence. $PostEmergency_t$ takes value 1 after September 2014. The end-level of public good provision is a measure of the ideal level of health centers if the great amount of financial aid was available at the beginning of the outbreak. This is given by $NearETU_i^{end}$, which is the normalized inverse distance to the closest treatment center ever available to a given location. Our main effects of interest are first γ_1, which measures the impact of new infections on conflict incidence for locations with high potential demand for public goods, before the arrival of the main package. Secondly, γ_2, which gives us the effect for these locations, after the arrival of health centers. We expect $\gamma_1 > 0$ if there is a high demand for those public goods and or there are rumors surrounding the few treatment centers that are present. Moreover, we expect $\gamma_2 < 0$, if the arrival of public goods lowers the incidence of social unrest.

A potential confounder is the epidemic itself. If only locations with a sufficient level of Ebola have conflict incidence, access to treatment centers could be picking up this effect. We therefore control for the cumulative level of Ebola and also add another term to our specification, which would capture differential effects for high and low infected regions, $ebola_{i,t-1} \times HighEbola_i^{end}$ and $ebola_{i,t-1} HighEbola_i^{end} \times PostEmergency_t$, as well as $HighEbola_i^{end} \times PostEmergency_t$ for consistency with a fully specified model.

The main results are summarized in Table 2.9. There is a lower incidence of conflict due to the epidemic after a significant amount of aid arrives in the ground, column (1). Prior to this moment, the epidemic causes civil violence in locations with a high demand for Ebola Treatment Units (ETUs), column (2). The effect is three times larger for locations with high demand of public goods, than the average effect, 0.037 compared to 0.012. However, after this, there is a drop in civil violence. The estimates are stable when we control for cumulative Ebola cases or allow for heterogeneous effects for high and low incidence areas, Tables B.25-B.26. They are also stable when controlling for other public goods, column (5) in Table 2.9. The impacts are of similar magnitude and sign for

Laboratories, but not statistically significant, column (3). This is consistent with the role of rumors in fueling distress around ETUs before there are enough of them. Moreover, ETUs are for patient care and suppose a more immediate benefit, whereas laboratories are for prevention of future spread, therefore implying benefits that are deferred. Community Care Centers (CCCs) have the opposite sign but are not precisely estimated. These were local hospitals that were spontaneously turned into first patient care for Ebola patients. We interpret this as suggestive evidence, that wherever the state or the international organizations cannot reach, this leads to social unrest and potentially allows people to organize to develop own strategies within the local community (Richards, 2016).

A simple correlational exercise studying whether conflict throughout the epidemic predicts access to ETUs, laboratories or Community care centers, shows that areas with higher conflict incidence during the Ebola outbreak also had higher access to CCCs. As expected, conflict incidence is not predictive of higher ETUs or laboratories, which are established by international organizations with the objective to halt the spread of Ebola. These results are summarized in Table B.27. We interpret the combination of these findings as indicative of subversive violence arising in demand of public goods.

Table 2.9: Public Goods: Heterogeneous effects with Health Centers

Outcome: conflict(t)	(1) conflict(t)	(2) conflict(t)	(3) conflict(t)	(4) conflict(t)	(5) conflict(t)
ebola(t-1)	0.0220***	0.00214	0.0195**	0.0301	0.0140
	(0.0071)	(0.0039)	(0.0079)	(0.0192)	(0.0098)
ebola(t-1) × PostEmerg	-0.0177***	-0.00343	-0.0157***	-0.0309	-0.0172*
	(0.0059)	(0.0039)	(0.0056)	(0.0194)	(0.0102)
ebola(t-1) × NearETU^{end}		0.0368***			0.0376***
		(0.0052)			(0.0093)
ebola(t-1) × PostEmerg × NearETU^{end}		-0.0209***			-0.0226**
		(0.0055)			(0.0087)
ebola(t-1) × NearLab^{end}			0.0270		0.00133
			(0.0360)		(0.0369)
ebola(t-1) × PostEmerg × NearLab^{end}			-0.0188		0.00789
			(0.0378)		(0.0386)
ebola(t-1) × NearCCC^{end}				-0.0102	-0.0154
				(0.0211)	(0.0099)
ebola(t-1) × PostEmerg × NearCCC^{end}				0.0178	0.0175*
				(0.0209)	(0.0101)
N	36480	33516	33516	36480	33516
R2	0.010	0.013	0.012	0.010	0.014

(Clustered SE) by Dist; Excl. capital; only Epidemic period; Time FE, Chiefd FE, Reg × Month FE
Omitted: ETU*PostEmerg, Lab*PostEmerg, CCC*PostEmerg
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of cases in 100'000 per capita. $PostEmerg$ is a post-treatment dummy taking value 1 after September 2014, when a great amount of emergency assistance is released. $NearETU_i^{end}$ is the normalized inverse distance to the closest Ebola treatment unit (ETU) ever available to a given location. $NearLab_i^{end}$ is the normalized inverse distance to the closest Laboratory for rapid testing of the Virus ever available to a given location. $NearCCC_i^{end}$ is the normalized inverse distance to the closest Community Care Center (CCC) ever available to a given location.

Trust levels and Religious beliefs

Here we study the role of trust and religious beliefs as determinants of civil violence in the context of an epidemic. The epidemic requires a change in cultural practices and the adoption of new medical technologies to halt its spread. This moves institutional authorities to respond and induce a behavior change. Civil disobedience targeted at doctors or social workers, trying to stop the outbreak, suggests not only a role for state coercion and demand for public goods driving civil violence in the context of an epidemic, but also of misinformation or mistrust in authorities. Whether the state succeeds in inducing the required changes to halt the outbreak, depends on costs and benefits of cultural change. The imposition of safe burial practices has a larger cost for communities with strong religious beliefs. The perceived benefits of the change in practices depend on trust in authorities.

We approach this by looking into heterogeneous effects of new Ebola cases on conflict incidence for varying levels of trust or religiosity in a given location[55]. The effect of interest are new infections interacted with each of our covariates. We control for new infections interacted with the distance to the epicenter and square distance in order to diminish the threat that we are capturing differences in cultural traits due to the random event of the first index case arising in a particular location, or differences due to the epidemic generating more distress for locations that were hit first[56]. We construct summary index statistics to group several variables of interest, following Anderson (2008). The covariates are constructed from survey data from the Afrobarometer and measured pre-epidemic and aggregated at the the level of our unit of observation, i.e. chiefdom, district and sub-prefecture for Sierra Leone, Liberia and Guinea, respectively. The results should be interpreted with caution due to the small sample size per cell, namely around 28 surveyed individuals on average in each of our locations. We adjust our p-values for multiple inference following Anderson (2008), Tables B.31-B.32.

[55] To study heterogeneous effects we start from our baseline high frequency panel specification. We are interested in teasing out patterns in the data, based on pre-existing covariates. Equation (2.8) summarizes the specification.

$$\begin{aligned} conflict_{i,t} =& \beta_0 ebola_{i,t-1} + ebola_{i,t-1} \times \sum_{k=1}^{K} \beta_k Covariate^k \\ &+ \gamma_1\ ebola_{i,t-1} \times DistEpic_i + \gamma_2\ ebola_{i,t-1} \times DistEpic_i^2 + \alpha_i + \lambda_t + \mu_{r,\tau} + \epsilon_{i,t} \end{aligned} \tag{2.8}$$

We are interested in β_k, the impact of new infections in areas with a greater share of covariate k. The overall effect of new infections on civil violence is $\sum_{k=0}^{K} \beta_k + \sum_{j=1}^{2} \gamma_j$.

[56] We used distance and square distance as an instrument for the total cumulative number of infections in Subsection 2.4.1 when looking at the overall effect of the epidemic on conflict incidence, in the difference-in-difference strategy. In this case we are in our high frequency panel specification looking at impacts of new Ebola infections every two weeks, conditional on fixed characteristics. The distance to the epicenter is a fixed characteristic that is predictive of the spread of Ebola in the long-run. The interaction of new Ebola infections with the distance to the epicenter will capture this potential for long-run spread. By controlling for it, we are studying the impact of new Ebola infections on conflict incidence for locations varying under a given dimension, conditional on their potential long-run spread.

The main results are presented in Table 2.10. The most robust result across specifications is that locations with low trust in leaders have higher rates of civil violence as a consequence of the epidemic, columns (4)-(5). This holds across specifications and controls. This is consistent with low trust in institutional authorities leading to lower health uptake. We see a positive coefficient on high trust in local institutions in column (4), but this effect depends on the specification. The coefficient is not statistically different from zero when we control for other variables, column (5).

Strong religious beliefs are associated with a greater likelihood of civil violence as new Ebola cases emerge, columns (1), (2), (5). These areas are not more violent at baseline, however, Table B.29. There is no difference when looking at differences across the three most prevalent religions in the affected countries. This is consistent with the fact that people from any religion face costs to cultural changes[57].

We also study other expected correlates of civil violence, such as ethnic diversity and potential income channels. Ethnic polarization is associated with a higher likelihood of civil violence, columns (3) and (5) in Table 2.10. We construct a summary index statistic for ethnic salience, grouping questions on ethnic rather than national identification and perceived discrimination of the own ethnic group. We find that ethnic salience has no effect, columns (3) and (5). Note that ethnic fractionalization and polarization are measures of the distribution of ethnic groups and they do not necessarily capture ethnic cleavages[58]. Prior conflicts and political grievances have little explanatory power in this

[57]Safe burial practices that were imposed could be more costly for traditional African beliefs, or Muslims, due to the custom of family members washing the deceased, but also cremations, traditionally against Christian views, were imposed in Liberia, which has a Christian majority.

[58]Fractionalization is a Hirschman-Herfindahl index, given by $F = \sum_{i=1}^{m} n_i(1 - n_i)$, where m number of groups, (n_i, n_j) size of each group. It ranges from 0, with all people belonging to the same group, to 1, total diversity. The simplest measure of polarization is given by $P = \sum_{i=1}^{m} n_i^2(1 - n_i)$. It takes its maximum value when two equally sized groups face each other. They are negatively correlated at low values of fractionalization, not correlated at intermediate values and positively correlated at positive values.

Table 2.10: Correlates of civil violence

Outcome: conflict(t)	(1)	(2)	(3)	(4)	(5)
ebola(t)	0.0133**	0.0132**	0.0218***	0.0195***	0.00320
	(0.0053)	(0.0054)	(0.0062)	(0.0031)	(0.0052)
ebola(t-1) × Strongly Relig.	0.00314*	0.00358**			0.00557**
	(0.0016)	(0.0018)			(0.0028)
ebola(t-1) × Tradit. Relig		0.0000767			0.0000973
		(0.0001)			(0.0001)
ebola(t-1) × Ethnic Fractional.			-0.0519**		-0.0333
			(0.0231)		(0.0231)
ebola(t-1) × Ethnic Polariz.			0.0546**		0.0841***
			(0.0256)		(0.0284)
ebola(t-1) × Ethnic Salience			0.00942		0.0108
			(0.0103)		(0.0111)
ebola(t-1) × Trust Leaders				-0.0199**	-0.0323***
				(0.0075)	(0.0106)
ebola(t-1) × Trust Local Instit.				0.0230***	0.0161
				(0.0064)	(0.0101)
ebola(t-1) × Trust President				-0.00479	-0.00706
				(0.0058)	(0.0058)
ebola(t-1) × Trust Opposition				0.00247	-0.00740
				(0.0098)	(0.0126)
ebola(t-1) × Trust Army				-0.0228***	0.00411
				(0.0081)	(0.0126)
ebola(t-1) × Trust People				0.000379	0.00187
				(0.0014)	(0.0015)
Mean	0.0968	0.0968	0.0968	0.0968	0.0968
N	24852	24852	24852	24852	24852
R2	0.0508	0.0508	0.0510	0.0518	0.0528
Time FE	Y	Y	Y	Y	Y
Chiefd FE	Y	Y	Y	Y	Y

(Clustered SE) by Dist; Time, Chiefd; Control: ebola × DistEpic, ebola × DistEpic^2; Excl. capital
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. *ebola* is the number Ebola cases in 100'000 per capita. The covariates are Afrobarometer data measured pre-epidemic and aggregated at the level of our unit of observation, i.e. chiefdom, district and sub-prefecture for Sierra Leone, Liberia and Guinea, respectively. Ethnic salience is a summary index statistic grouping questions on ethnic rather than national identification and perceived discrimination of the own ethnic group. Strongly religious is the perceived importance of religion. Traditional religion is a religion that is a traditional African religion and is neither a branch of Islam nor of Christianity. Trust in people is a summary index statistic grouping trust in neighbors, in other citizens, family members.

context, as we see from studying prior voting outcomes, expressed political views for the incumbent or the opposition or conflict incidence during the Civil Wars in Liberia and Sierra Leone, columns (3) and (5), or Table B.30. The prize of the riot is a public good, for instance it can defeat a military quarantine. In this case polarization should matter more than fractionalization according to a theory proposed by Esteban and Ray (2011a).

To rule out that possible income channels are driving the main results, we look at the impact of the epidemic on conflict incidence for varying levels of wealth and we also study whether food prices drive our results. The aim of this exercise is to rule out that pre-existing wealth or varying prices are the only drivers of civil violence in the context of an epidemic. The impact of the epidemic on civil violence does not change by the inclusion of contemporaneous food prices, Table B.28. This suggests that changing economic conditions measured (imperfectly) in price levels of two important commodities for food consumption (imported rice and palm oil) are not driving the results, for areas for which we have data on prices. We also study the role of pre-existing infrastructure in interaction with Ebola incidence and see that worse infrastructure is not associated with more civil conflict, Table B.30.

2.4.3 Long-run Impacts on Trust

The epidemic changes the relationship with the state, affects beliefs, and a costly change can potentially undermine trust in institutions. We study the long-term impacts on trust in institutions comparing two rounds of Afrobarometer survey data, pre and post-Epidemic. The effects on long-run trust are studied in a simple difference-in-difference strategy, comparing trust before and after the Ebola outbreak for locations with varying levels of Ebola incidence. If the epidemic affects conflict incidence through a change in citizens' perceptions of the state, we expect a drop in trust levels. We look at the impact of the epidemic on trust for areas with strong religious beliefs in third differences. If cultural change is a major source of social distress, we should be expect a further drop in

Table 2.11: Trust Levels Pre/Post Ebola

Outcome: Trust in	(1) Leaders	(2) Local Institutions	(3) President	(4) Opposition	(5) Army
PostEbola	-0.730***	-0.206***	-0.203***	0.0378	-0.126**
	(0.153)	(0.044)	(0.057)	(0.052)	(0.055)
EbolaTotal^{pc} × PostEbola	-0.000254	0.0000145	-0.000811**	0.0000942	0.000210
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Mean	2.55	1.47	1.85	1.29	1.73
N	457	457	457	457	457
R2	0.67	0.80	0.81	0.70	0.71

(Clustered SE) by Chiefd*Year; Chiefd FE
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: We compare two rounds of Afrobarometer data, pre and post-Epidemic. $EbolaTotal^{pc}$ is the total cumulative number of Ebola cases measured at the end of the epidemic in 100'000 per capita. $PostEbola$ is a post-treatment dummy taking value 1 from 2014 on.

trust levels for groups with high costs of cultural adaptation.

Results are shown in Table 2.11. Simple correlational evidence shows that there are lower levels of trust in leaders, in local institutions and in the President after the epidemic, compared to one or two years prior (first row). In difference-in-differences we find that areas that were harder hit by the epidemic experience a drop in trust in the President, column (3). We further look at interaction effects with levels of religiosity as measured prior to the outbreak, Table 2.12. The epidemic leads to a drop in trust in leaders for areas that are strongly religious, third row in column (1).

A potential implication of these findings is that epidemics affect weak institutional settings through their impact on social unrest and trust levels, especially for groups with significant costs of cultural adaptation. State coercion and weak public good provision exacerbates this effect and since lower trust in authorities is associated with more civil violence, especially among these groups, this widens the cleavage between them and the state authorities.

Table 2.12: Trust Levels Pre/Post Ebola - interaction with Religiosity

	(1)	(2)	(3)	(4)	(5)
Outcome: Trust in	Leaders	Local Institutions	President	Opposition	Army
PostEbola	-0.855***	-0.241***	-0.431***	0.197***	-0.168***
	(0.168)	(0.067)	(0.091)	(0.060)	(0.059)
$EbolaTotal^{pc} \times$ PostEbola	0.000536	0.000142	-0.000312	-0.000310	0.0000808
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
StronglyRelig $\times$ PostEbola	0.244	0.0690	0.439***	-0.307***	0.0814
	(0.290)	(0.093)	(0.106)	(0.084)	(0.108)
$EbolaTotal^{pc} \times$ StronglyRelig $\times$ PostEbola	-0.00229**	-0.000268	-0.000483	0.000559	0.000783
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Mean	2.55	1.47	1.85	1.29	1.73
N	457	457	457	457	457
R2	0.68	0.80	0.83	0.72	0.72

(Clustered SE) by Chiefd*Year; Chiefd FE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: We compare two rounds of Afrobarometer data, pre and post-Epidemic. $EbolaTotal^{pc}$ is the total cumulative number of Ebola cases measured at the end of the epidemic in 100'000 per capita. $PostEbola$ is a post-treatment dummy taking value 1 from 2014 on.

2.4.4 Robustness checks

We provide a number of robustness checks on our high-frequency panel specification (2.4). Firstly, the main concern to our OLS specification is unobserved serial correlation in conflict or the possibility of conflict affecting the future spread of Ebola. We address these concerns with a number of strategies leading to similar results.

In all our specifications we cluster standard errors at a given region or location, allowing for time dependency. For robustness we add cumulative Ebola and past Ebola cases and lagged conflict as control $X_{i,t-j}$ and show that our coefficient of interest β is stable. Given that we have many time periods and that we study the impact of infections, conditional on several lags in our explanatory variable, the inclusion of a lagged dependent variable is unlikely to affect our coefficient of interest significantly[59]. The Jorda local projection specification also addresses these concerns including several lags in Ebola and conflict incidence and clustering standard errors at a given location.

We also run an OLS regression of conflict on Ebola incidence with flexible coefficients on

[59]The limited influence of lagged dependent variables on other covariates of interests in long panels has been shown using Monte Carlo simulations by Judson and Owen (1999); Beck and Katz (2004).

past and future infections to show the full dynamics. The strategy is shown in equation (2.9).

$$conflict_{i,t} = \sum_{j=-J}^{J} \beta_j \; ebola_{i,t+j} + \alpha_i + \lambda_t + \mu_{r,\tau} + \epsilon_{i,r,t} \tag{2.9}$$

Since $ebola_{i,t+j}$ for $j \geq 0$ are post-treatment variables affected by our explanatory variable of interest, $ebola_{i,t-1}$, they are bad controls and our coefficient of interest β_{-1} is likely to be biased under this specification. Therefore, our main specification does not include future Ebola incidence. We provide OLS results for equation (2.9) as a placebo exercise strengthening our results. In particular it allows us to test whether future Ebola is predictive of conflict today, when we condition on past Ebola incidence.

Furthermore, we test whether conflict incidence generates new Ebola infections in the future by estimating equation (2.10).

$$\begin{aligned} ebola_{i,t} &= \rho \; ebola_{i,t-1} + \beta_0 \; conflict_{i,t-1} \\ &+ \beta_1 \; conflict_{i,t-1} \times ebola_{i,t-1} + \alpha_i + \lambda_t + \mu_{r,\tau} + \epsilon_{i,r,t} \end{aligned} \tag{2.10}$$

In particular, conflict cannot generate new infections unless there are already Ebola infections, since all infections after the single first index case were through human-to-human transmission. We also know that this needs to occur within the two weeks in which an infected individual has symptoms. Therefore our coefficient of interest is β_1 and we expect β_0 not to be statistically significantly different from zero.

On the other hand, we can also allow for the possibility of dynamic effects estimating a dynamic panel by General Method of Moments (GMM). Causal inference in a dynamic model relies on the weaker assumption that new infections are pre-determined with respect to conflict. That is, while conflict could cause future infections without challenging our identification, the important identifying assumption is that, conditional on controls, conflict is not correlated with new infections in the past, for reasons unrelated to the epidemic. The identifying assumption in a dynamic model with serial correlation in conflict up to $l > 0$ lags is summarized in equation (2.11). It gives us a long list of moment conditions used to estimate equation (2.4) by GMM.

$$E(\epsilon_{t,i}|ebola_{i,t-j}, X_{i,t-j}, \alpha_i, \lambda_t, \mu_{r,\tau}) = 0 \text{ for } j \geq l \text{ (but not for } j < l) \tag{2.11}$$

Secondly, we provide an empirical strategy that addresses the possibility of time-varying unobservables driving the correlation between new infections and conflict incidence within the same location. The number of new infections in a given location is instrumented with the presence of the epidemic in neighboring locations. In particular, our instrument is a dummy variable taking value 1 if there is any case in neighboring chiefdoms and 0 otherwise. We measure this at time $t-2$, a period prior to the Ebola cases of interest and also at times $\{t-2, t-3, ..., t-10\}$, to allow for more flexibility in the impacts changing over time. We allow for the effect to vary for distinct countries, for capitals, capital-districts and other locations. The exclusion restriction is that the presence of the epidemic in neighboring areas does not drive conflict in a given area either than through its impact on the epidemic. We provide evidence to support this hypothesis by showing that there are no spillover effects when looking at the number of Ebola cases in neighboring chiefdoms, conditioning or not for own cases. We add a dummy variable indicating whether there is conflict or not in the region except the own as control in our 2SLS specification. Although unobserved spillovers are always possible, this instrument addresses the possibility that time-varying unobservables in the own location are driving our results.

Thirdly, to address the possibility of non-standard measurement error in infections, we use a second instrumental variables strategy. In particular, we instrument new infections with past infections or with predicted infections from the medical literature. The predicted number of cases is created following Fang et al. (2016)[60]. The model takes into account the

[60]We thank Fang et al. (2016) for sharing their code and data to replicate the Poisson transmission model in their paper. We modify the code in order to remove potential confounders and to generate out-of-sample predictions in Ebola infections.

location and time of the first index case and the position of each chiefdom in the geographic network, to estimate the parameters determining the rates of infection between distant, neighboring and own chiefdoms in Sierra Leone by Maximum likelihood. Infections follow a Poisson process and a number of covariates enter non-linearly multiplying the exponent of the risk ratio. We modify their code to do out-of-sample predictions in Ebola infections and remove potential confounders. The covariates we include are either fixed over time and measured prior to the start of the outbreak, or only vary over time for the whole country[61]. Our location and time fixed effects would remove their main effect. The identifying variation in this instrument comes from the position in the network of each chiefdom and the arrival of past Ebola infections[62]. We instrument $ebola_{i,t-1}$ in (2.4) with the resulting measure of predicted ebola cases. Since the exact timing of Ebola infections are hard to predict, even ex-post, we need past Ebola cases to predict future cases. The most conservative predictor is using Ebola infections four weeks in the past to predict current infections. That is, the exclusion restriction of the instrument is a weaker version of the fact that past infections should not affect civil violence in the future either than through its impact on current infections. Given the short-run dynamics of EVD and that we find only immediate impacts of Ebola on future conflict incidence using the actual number of Ebola cases for a variety of specifications, we think that this instrument addresses at least our main concern. Namely it allows us to address measurement error,

[61] The original covariates included in the model are population density, weekly average temperature and relative humidity (varying at national level only), treatment centers, distances to nearest primary roads, secondary roads, railroads, distances to the nearest hospital, coverage percentages of cropland, forest and shrub, poverty level, three broad intervention phases and primary ethnic groups. We remove obvious confounders from the model.

[62] The model is explained in the Appendix to Fang et al. (2016). We provide here a summary. Let $Y_i(t)$ be number of symptom onsets in chiefdom i during week t. $Z_i(t) = \sum_{d=1}^{D} \omega_d Y_i(t-d)$ are infectious cases. These are cases that have not developed symptoms yet are therefore not able to infect other people. The probability of infectiousness being d, i.e. within 21 days is given by ω_d. The number of Ebola cases we observe are $Y_i(t)$. They follow a Poisson process, $Y_i(t) \sim Poisson(N_i \gamma_i(t))$. Where N_i is population size in chiefdom i and together with $\gamma_i(t)$ gives us the average probability of a new case arriving in chiefdom i at time t. It depends on cases arriving in the own chiefdom i, neighboring chiefdoms j and distant chiefdoms, as well as on the transmission rate and either pre-determined covariates or if time-varying only changing at national level. We remove other covariates. The model used is $\gamma_i(t) = \{\gamma_0 + \gamma_1[Z_i(t) + \theta \sum_{j \in B_i} Z_j(t)]\} e^{\beta' X_i(t)}$. The model is estimated by maximum likelihood. We choose initial values for γ_0^0, γ_1^0, θ^0, and estimate $\hat{\beta}^k$ after k iterations. Given β^k, we maximize the Poisson likelihood, to obtain $\hat{\gamma_0}^k$, $\hat{\gamma_1}^k$, $\hat{\theta}^k$.

reverse causality and serial correlation in conflict incidence.

Finally, newspaper bias is a potential problem when working with the widely used ACLED dataset. We think that the high-frequency panel specification significantly reduces the threat of newspaper bias driving the results. In particular, journalists would have to perfectly predict the epidemic spread[63] and move strategically every two weeks into areas with high Ebola incidence, in order to generate a positive correlation between infections from medical records and reported conflict at two-week frequency. We give a full list of newspapers reporting in the two year prior (2012-2013) and during the epidemic (2014-2015), Supplementary Appendix Tables D.4-D.6. There is some turnover of newspapers reporting comparing both periods. Our main empirical strategy addresses this potential concern by exploiting high-frequency variation within locations. Shut-down of newspapers is taken into account with our time fixed effects. Region $\times$ month fixed effects further take out the variation that might arise at regional level at monthly periods.

Results on Robustness Checks

The main results to various specifications discussed above are summarized in Table 2.4 for all countries. The results are stable across specifications, positive and statistically significant. We have slightly smaller results in our GMM estimation strategy and slightly larger results from the 2SLS specification with neighboring chiefdoms, but similar in magnitude. The point estimates vary from $0.008 - 0.02$, implying a $6 - 15\%$ increase in the likelihood of conflict incidence over the next few weeks due to one additional Ebola case in 100'000 per capita. The reduced form estimates and first stage results using the presence of the epidemic in neighboring locations in the last period only are shown in Table B.11. We find no geographic spillovers, Table B.18.

A simple difference-in-difference strategy exploiting the arrival of the first case in each

[63]This is very hard, even ex-post for epidemiologists.

location and the total end-number of Ebola cases in that location shows an overall effect in conflict incidence of 1% per two-week period for one single additional Ebola case in 100'000 per capita, Table B.10. A similar strategy to the difference-in-difference design exploiting the first case in each country is done at sub-national level in Figure B.7, using the time of arrival in a district and the total Ebola incidence in a given chiefdom[64].

Results for Sierra Leone are given in Table 2.13, for which we have constructed predicted Ebola infections as instrument following the medical literature (Fang et al., 2016)[65]. The impacts are consistent across specifications, with point estimates varying from $0.010-0.017$. The baseline incidence of conflict is much smaller in Sierra Leone and these point estimates imply a $21-36\%$ increase in the likelihood of conflict from a baseline mean (standard deviation) incidence throughout the epidemic of 0.047(1.30), or much larger in comparison to pre-epidemic incidence, 0.012(0.50). The first stage fit for column (5), using the predicted Ebola from the medical literature, is shown by plotting the raw data of new Ebola cases and predicted Ebola, Figure B.10.

We interpret the slightly larger 2SLS coefficients found with instruments using distinct types of variation, such as the distance to the epicenter in the difference-in-difference strategy, the presence of the epidemic in neighboring locations and predicted Ebola from the medical literature as an indication that OLS results are biased downwards due to measurement error in the number of infections. Our preferred specification are the OLS results, since they are more conservative estimates and they reflect the impact of confirmed and probable cases on civil violence. As we will discuss in the Section on drivers, the effect of the epidemic on civil violence changes over time and space as the state response evolves. The smaller effect in the GMM strategy could mean that there are feedback effects, in the sense that conflict amplifies Ebola incidence in the future. We will study this now in detail.

[64]This is also shown for Guinea, for which we have sub-prefecture level data in Ebola cases, Table B.6, but not for Liberia, for which we only have county-level data in Ebola incidence (14 counties).

[65]We are still working on extending it to Guinea and Liberia

Table 2.13: High-frequency panel: Summary of Results for Sierra Leone

Outcome: conflict(t)	Sierra Leone				
	(1) OLS	(2) OLS	(3) GMM	(4) IV-eb(t-2)	(5) IV-Pred.eb
ebola(t-1)	0.0141***	0.0128**	0.0102**	0.0153***	0.0172**
	(0.0054)	(0.0052)	(0.0109)	(0.0058)	(0.0081)
N	15369	15218	15369	15218	15369
R2	0.050	0.052		0.050	0.050
Time FE	Y	Y		Y	Y
Chiefd FE	Y	Y		Y	Y
Clusters	Chiefd	Chiefd		Chiefd	Chiefd
Controls					
ebolaCum		Y			

(Robust SE)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of Ebola infections over time. Column (3) estimates a dynamic panel of conflict on past Ebola using all possible lags as GMM-type instruments for the difference equation. Column (4) uses $ebola(t-2)$ as instrument for $ebola(t-1)$. Column (5) uses predicted Ebola following (Fang et al., 2016). The First stage is shown graphically in Figure B.10.

Results for a regression including several lags and leads in Ebola, equation (2.9), are shown in Tables B.12- B.13 and Figure B.11. As mentioned this cannot be our main specification since future cases are bad controls, they are affected by our variable of interest. However, this serves as a placebo exercise to show that reverse causality is not driving our results. They indicate that infections in the past two weeks lead to a rise in civil violence and that conditional on these, leads have no bite. The F-test shows that only past cases are statistically significantly different from zero, while leads are not.

We study the possibility of conflict incidence directly affecting the spread of Ebola, Table B.15. First we show that adding a lag in conflict incidence does not affect our coefficient of interest[66]. Moreover, the lag is not significant and there is no evidence of serial correlation.

[66]The limited influence of lagged dependent variables on other covariates of interests in long panels has been shown using Monte Carlo simulations by Judson and Owen (1999); Beck and Katz (2004). In particular, without the covariates the bias derived by Nickell (1981) is $plim_{N\to\infty}(\hat{\rho}-\rho) \approx \frac{-(1+\rho)}{T-1}$, with ρ being the relationship between conflict at time t and conflict at time $t-1$. We have $T = 115$ two-week periods and $\hat{\rho} = 0.053$, so the bias in $\hat{\rho}$ is $\frac{-(1+0.053)}{114} \approx -0.009$. This is an upper bound, since the inclusion of covariates necessarily reduces this bias (Nickell, 1981). It affects our coefficient of interest indirectly through the first-stage correlation between lagged conflict and Ebola incidence, estimated to be 0.06. An

Results for a Wooldridge (2002) test for autocorrelation in panel data suggest no evidence of serial correlation in conflict incidence, Table B.14. Second, we test whether the spread of Ebola is affected by conflict incidence, as explained above, equation (2.10). We find no evidence of this feedback effect, Table B.15.

Finally, our results are robust to using as outcome variable conflict incidence as a dummy variable taking values in $\{0, 1\}$, as well as using as an explanatory variable the total number of new Ebola cases including suspect cases, Table B.16, or using count data models, Table B.17.

2.5 Conclusion

The emergence of infectious diseases has been increasing in the last decades and they are likely to rise in the future as globalization, population growth, environmental degradation and climate change are affecting human societies and the natural environment in ways never experienced before[67]. Extraordinary advances in the medical science have allowed the international community to intervene in such contexts. The perception of disease epidemics as a threat to global security, beyond its impacts on human health,[68] however, shapes the objectives and implementation of emergency assistance. The international community is often accused of intervening too late, once the risks of a pandemic are undeniable[69], and of implementing draconian measures, intended for containment, rather than minimizing the impact of an epidemic on the local population[70].

upper bound to the bias in our coefficient β is $-0.06 \times (-0.009) \approx= 0.00054$ or 4% of our estimated $\hat{\beta} = 0.0127$ in the regression of conflict on ebola incidence with lagged conflict as control. Taking this into account, the lower bound impact of new ebola infections on conflict incidence is 0.0122.

[67](UNICEF/UNDP/WorldBank/WHO, 2004; Jones et al., 2008)

[68](WHO, 2016)

[69]"The lack of international political will was no longer an option when the realisation dawned that Ebola could cross the ocean. When Ebola became an international security threat, and no longer a humanitarian crisis affecting a handful of poor countries in West Africa, finally the world began to wake up," Dr Joanne Liu, MSF international president.

[70]"Whilst social unrest and fears of state collapse ran rampant, we feared that our call [for civilian and military assets with expertise in biohazard containment] would be misconstrued or intentionally twisted into a call for armed stabilisation", Christopher Stokes, MSF general director.

In this paper we provide empirical evidence that these interventions can potentially affect civil violence in developing countries. We identified numerous acts of civil violence reported in newspapers, following the spread of cholera, Malaria, HIV/AIDS, in Congo, DRC, Haiti, Kenya, Nigeria, Mozambique, Uganda, Tunisia, Somalia, South Africa[71]. We take the case of the recent Ebola epidemic in Western Africa to provide empirical evidence of epidemics leading to riots, protests and civil violence against government authorities, medical personnel and social workers trying to contain the outbreak, and provide precise mechanisms underlying this effect.

The impacts are large, immediate and have long-run consequences on trust in institutional authorities. Our results show that the effects are tied to the emergency response, pre-existing levels of trust and barriers to cultural adaptation. A new infection in 100,000 per capita raises conflict incidence by 10% in a given location, from a baseline mean incidence of 0.0128 in 100,000 per capita at two-week level. Moving from no cases to the average number of infections for epidemic areas at the start of the outbreak roughly doubles the incidence of conflict within two weeks. Our results suggest that state coercion, demand for public goods and little sensitivity to local cultural practices are determinants of civil conflict. We find the largest impacts of the epidemic on civil violence around the beginning of the international response, when safe burial practices were imposed. Areas with low trust in leaders and strong religious beliefs, are more likely to engage in such subversive violence, as they face higher costs of cultural change. State capacity has a large impact on civil violence in this context. We find large impacts of military district quarantines on increasing the likelihood of riots and protests, beyond and independently of the impact of new infections. The results are driven by areas with high demand for health treatment and access to it lowers conflict incidence, driven by areas closer to them. The epidemic led to lower trust in institutional authorities, especially for strongly religious communities.

Epidemics in which the state intervenes or is expected to intervene alter citizens' perception and demands from the state. Halting an epidemic leads the state to adopt coercive

[71] The Armed Conflict Location and Event Data Project, 1997-2015.

measures, it generates a demand for public goods and it requires a change in cultural practices. These changes lead to social unrest, depending on the coerciveness of the response, the capacity of the state to contain the outbreak, trust in institutional authorities and beliefs among citizens. These channels also mean that epidemics are more likely to lead to civil conflict in weak institutional settings, with low trust, weak public health systems and state coercion that is perceived as illegitimate. Moreover, depending on the state response, they lower trust in institutional authorities, therefore further weakening the state.

These findings have policy implications, as they inform the choice of emergency assistance. In particular, coercive measures, little sensitivity to local customs and a late intervention lead to social unrest, undermine containment efforts (Chapter 3) and have long-run effects on trust.

The possibility to track a shock from the first index case to the last contagion, an exogenous shock in state capacity generated by the influx of emergency assistance, combined with our fine-grained data and knowledge of the context and circumstances leading to civil violence, allow us to advance in our understanding of conflict in weak institutional settings.

Chapter 3

Local Media and the Spread of Ebola: Evidence from Guinea

"Chinoziva ivhu kuti mwana wembeva anorwara."

(It's the people close to someone that know her/his affairs).

Tsumo (Shona Proverb)

3.1 Introduction

The Ebola epidemic in West Africa in 2014-16 caused local devastation and global alarm. In the most affected countries, Guinea, Liberia and Sierra Leone, over 28,616 people were infected, among which 11,310 died[1], leading to social unrest and economic losses estimated to US$2.2 billion in 2015 alone[2]. Weak local medical infrastructure was quickly overwhelmed, predictions went up to over one million of infected people without further action[3] and as smaller outbreaks emerged in other parts of Africa and cases were exported to Europe and the United States, the fear of a pandemic escalated. The international community eventually recognized it as a global health emergency[5] and injected

[1] `http://www.who.int/csr/disease/ebola/en/`, accessed April 1, 2017.

[2] World Bank 2016, World Bank Group Ebola Response Fact Sheet `http://www.worldbank.org/en/topic/health/brief/world-bank-group-ebola-fact-sheet` accessed May 17, 2016

[3] The Center for Disease Control and Prevention (CDC) considered the possibility of a high risk scenario leading up to 1.4 million infected people by January 2015, echoed by newspapers[4].

[5] The WHO has been widely criticized for acting too late, eight months into the epidemic, and later acknowledged this as a mistake (WHO, 2016). Doctors Without Borders (MSF) required assistance

emergency assistance worth US$459 million[6], including financial resources, medical technology and infrastructure and military aid, coordinated under the auspices of the World Health Organization (WHO). While this influx of humanitarian aid was critical to halt the outbreak, there was another crucial element. A major issue for epidemic control was whether or not communities could change their approach to caring for the sick and burial of the dead (Richards, 2016). Hence, it required the social acceptance of implemented policies and new technologies and a rapid change in cultural practices. A question that emerged was how to possibly change cultural practices in a matter of months? Local, national and international actors tried many strategies, including a massive communication campaign. They designed radio programs informing, persuading or exhorting citizens to take protective measures, seek treatment and change burial practices. Can media influence cultural practices in a matter of months? And if so, what makes broadcast information particularly effective?

This paper seeks to identify the impact of media on the spread of Ebola. We conjecture that broadcast information serves as a coordination device to change cultural practices that facilitate the spread of disease. Using original data from Guinea and a quasi-experimental design based on exogenous variation in radio signal reception by distinct media outlets, combined with the precise timing of distinct information campaigns about Ebola, we study the effect of local radios on the spread of Ebola, social resistance and treatment uptake. We provide suggestive evidence of a coordination mechanism, rather than a pure information or persuasion effect, exploiting survey data on post-epidemic beliefs, knowledge and stated treatment uptake, on one hand, and measuring the change in burial practices in response to radio emissions or social mobilization campaigns, on the other.

from the international community in March 2014 and alerted that the epidemic was 'out of control' in June 2014. It was only in August 2014 that the World Health Organization (WHO) recognized it as an 'international public health emergency' and that the World Bank released emergency assistance funding of US$200 million, in addition to financial or material aid from international donors, materializing into infrastructure in the months to follow.

[6]The total worth of direct and in-kind contributions to WHO for the Ebola response was US$459 million from over 60 donors between March 2014 and 22 April 2016, `www.who.int/csr/disease/ebola/funding/en` updated April 2016

Several competing hypotheses have been advanced regarding the possible impact of information transmitted through radio on health behavior in particular or cultural practices more broadly. On one hand, some have argued that media campaigns have no effect in this context, e.g. Richards (2016) argues: "Devising safer practices is work for community groups, not radio propagandists." Galiani et al. (2016) found that mass media alone has no impact handwashing behavior, unless combined with more intensive community and school-level activities. More generally, the literature has found mixed evidence on the impact of information on health behavior, ranging from no effect (Kremer and Miguel, 2007; Duflo et al., 2015) to an effect depending on the type of information provided (Dupas, 2011). On the other hand, we also have evidence of media campaigns affecting divorce, fertility decisions and other core markers of gender equality (Chong and Ferrara, 2009; Jensen and Oster, 2009; La Ferrara et al., 2012). This paper seeks to contribute to this literature by giving light to a potentially important mechanism underlying the heterogeneity of results. Health behavior is often associated to cultural norms and we hypothesize that broadcast information, through its common knowledge aspect is more likely to affect certain protective behaviors, namely those that require a collective change, compared to other types of information. However, it should not have an additional impact on private actions, such as handwashing behavior, compared to private information. While theoretically appealing, it is not obvious that broadcast information would affect cultural norms in practice. Not all sources of information are necessarily trusted, given a long history of extractive institutions and oppression against local or traditional practices[7], or due to contradictory messages being disseminated, as scientific knowledge about Ebola evolved; or the information might be too hypothetical or difficult to follow[8]. Culture, moreover, is strikingly persistent under pressure of cultural transmission[9].

Set against several possibilities, estimating the causal impact of broadcast information on health behavior, cultural practices and the spread of a disease is challenging. Firstly, radio

[7](Nunn and Wantchekon, 2011; McGovern, 2012; Alsan, 2014; Morse et al., 2016)

[8]If we cannot touch the sick, how do we care for them?

[9](Cavalli-Sforza and Feldman, 1981; Putnam et al., 1994; Voigtländer and Voth, 2012; Alesina et al., 2013)

access is likely to be correlated with socio-economic, demographic and geographic factors related to the spread of the disease. Secondly, the information campaigns are potentially evolving endogenously to the change in behavior and the epidemic spread. Thirdly, the effect might be confounded with other interventions occurring simultaneously.

This paper addresses these questions using pre-epidemic signal exposure to a local radio, conditional on having access to other radios, and exploiting the centralized nature of Guinea, whose local radios officially started their Ebola program at the same time with roughly similar contents. The main empirical strategy follows the same logic as a standard difference-in-difference strategy with continuous treatment. We compare areas with varying access to distinct media outlets that pre-date the start of the epidemic, before and after a given information campaign starts several months after the beginning of the Ebola outbreak. More precisely we study the effect of having access to an information campaign aired in a local radio on the spread of Ebola. Other outcomes studied are resistance behavior and a measure of treatment uptake, namely the ratio of Ebola deaths in community compared to Ebola deaths in an Ebola Treatment Unit (ETU). The epidemiological data is from the WHO. Radio transmitter location and characteristics were provided by the telecommunications authority in Guinea (ARPT), while details on information campaigns were collected during in-person interviews and surveys conducted by the author to radios across Guinea. Identification relies on a parallel trends assumption, namely that areas with greater access to a given radio program would have behaved similarly to other areas in the absence of the information campaign. In fact, we not find only parallel trends, but also the same evolution of Ebola in areas with varying access to a rural radio from their own community, compared to areas with access to other rural radios, prior to the start of the rural radio campaigns[10].

Additionally, we provide a number of strategies, intended as suggestive, to test the main hypothesis, that local radios served as a coordination device to change behavior over

[10]The evolution of the disease does not follow parallel trends across other media outlets, such as national or private radio stations, prior to their own information campaigns, and we therefore omit their study.

time as individuals updated their beliefs about socially acceptable practices, which ultimately affected the spread of the disease. We are guided by a conceptual framework that borrows from the literature on global games and from epidemiological theory and closely follows Yanagizawa-Drott (2014). Firstly, we provide evidence that our measure of radio signal reception is correlated with ownership of radio devices and radio listening patterns, using survey data. We use Afrobarometer rounds 5 (2013) and 6 (2015), as well as a phone-survey conducted by Internews asking detailed questions to listeners of an Ebola program. Secondly, we exploit a survey conducted by the National Institute of Statistics in Guinea on post-Ebola beliefs and stated behavior to assess whether listening to an Ebola program on the media is related to greater knowledge about the disease and treatment uptake. We run a simple OLS and then use our radio signal measure as instrument for hearing about Ebola on the media. Thirdly, we exploit data from the Red Cross on weekly radio emissions, social mobilization campaigns, safe burials and refused burials to study in a panel estimation framework based on a Granger causality argument and selection on observables, whether radio emissions are followed by a change in burial practices. Finally, we discuss the role of local information in affecting beliefs and behavior change and provide evidence of a demand-side effect, compared to a supply-side effect of political accountability proposed in other settings (Besley and Burgess, 2002; Eisensee and Strömberg, 2007).

The results show that sustained access to a local radio program informing about protective measures, encouraging treatment, addressing Ebola rumors and new burial practices, lowered social unrest, affected treatment uptake and cut the epidemic significantly. While the spread of Ebola evolves similarly for several months comparing areas with and without access to a local radio, there is a drop in infected cases seven months after the start of the campaign. An increase by 10 percentage points in access to an own rural radio station is associated with a drop by $13 - 18\%$ in the number of Ebola cases after the seventh month following the start of the campaign. A back-of-the-envelope calculation suggests that around 303 Ebola infections could have been spared if all areas with access to a rural radio station had their own local radio from the beginning of the outbreak, that is 8% of the total number of Ebola cases. We see a concurrent drop in social resistance behavior, as well as a rise in treatment uptake, measured as the ratio of Ebola deaths in an Ebola treatment center (ETU) to deaths in the own community. We then provide empirical evidence intended as suggestive to test our hypothesis. Descriptive evidence shows that the constructed radio signal is correlated with ownership of radio devices and radio listening patterns[11]. Using survey data on beliefs and stated behavior, we find suggestive evidence of broadcast information affecting actions that are observed and punishable by others, such as seeking health treatment, but not private actions, such as the use of chlorine, which is more related to knowing a victim that had Ebola. Exploiting data on Red Cross activities over time we find that radio emissions in a given month are followed by less refused burials in the following month, but we do not see the same pattern for social mobilization campaigns, which do not have the common knowledge aspect necessarily. The results suggest that 20 additional radio emissions are needed to ensure one less burial refusal in the next month in a given prefecture. There is no evidence suggesting that public goods are provided ad-hoc to areas with higher exposure to local radios, therefore ruling out a pure supply-side effect. We conjecture that relevance of local information, trust in local institutions, language and proximity to the own ethnic group are mechanisms explaining the success of local radios compared to radios from distant communities, conditional on the same information provided.

Literature

This work contributes to several strands of literature. Firstly, this paper is related to the political economy of mass media (Strömberg, 2004). Compared to seminal contributions on the role of local media for greater provision of public goods, through greater political accountability (Besley and Burgess, 2002; Eisensee and Strömberg, 2007), the unique set-

[11] An increase by 10 in access to any radio signal is associated with a 25% increase in the ownership of radio devices and a 56% increase in the number of times they listen to news on the radio.

ting of the Ebola outbreak response, coordinated by external actors, allows us to credibly rule out this channel and focus on the demand-side effects of local media, i.e. its impact on the perception of the public goods provided[12].

A growing literature on the role of media to changing behavior shows that propaganda exacerbates sentiment and violence (DellaVigna et al., 2014; Yanagizawa-Drott, 2014; Adena et al., 2015) and that broadcast information can reduce social capital (Olken, 2009), improve long-term education in children (Gentzkow and Shapiro, 2008), influence fertility decisions (La Ferrara et al., 2012) and provide information to voters (DellaVigna and Kaplan, 2007; Ferraz and Finan, 2008; Casey, 2015). This paper contributes to this literature by providing evidence on the role of local media inducing a change in cultural practices, health uptake and the spread of disease in a matter of months.

This paper also contributes to this literature methodologically. While it is similar to previous literature on media that uses features of the geographic terrain and pre-existing exposure to radio signal reception to identify the effect of broadcast information on a relevant economic outcome, it adds two additional dimensions that strengthen the design. First, we add a time dimension, since we observe the Ebola outbreak for at least six months before the rural radio campaign starts. Secondly, we add a control group, namely areas that have access to information from other radio stations, or areas that have access to the same information campaign from other rural radio stations.

It also relates to a literature on cultural change and transmission. The importance of culture, a set of preferences, beliefs, and norms that govern human behavior to understand economic prosperity, has been widely documented (Greif, 1994; Manz et al., 2006; Fisman and Miguel, 2007; Gorodnichenko and Roland, 2016)[13]. While culture and the impact

[12]While a possible explanation for local media to impact the spread of Ebola could in theory be due to a greater provision of public goods through greater political accountability (Besley and Burgess, 2002; Eisensee and Strömberg, 2007), this is unlikely to be the main channel in this setting. The objective function of the whole apparatus set in place included the spread of Ebola only, the allocation of laboratories and Ebola treatment centers (ETUs) was allocated on medical grounds, first set up by international Organizations, such as MSF, and then coordinated under the auspices of the WHO. In fact, the intervention was criticized for taking little account of social unrest and local populations, as illustrated by the imposition of quarantines and cremations in Liberia (Moon, 2015).

[13]For recent reviews see Bisin and Verdier (2011); Gershman (2017)

of institutions on culture is strikingly persistent (Putnam et al., 1994; Acemoglu and Robinson, 2001; Nunn and Wantchekon, 2011; Voigtländer and Voth, 2012; Alesina et al., 2013), there is also evidence of a change in culture in a matter of decades, following institutional variation, (Alesina and Fuchs-Schundeln, 2007; Fernández, 2010; Fernández-Villaverde et al., 2014). However, sometimes apparently inefficient cultural norms persist under pressure of cultural transmission (Cavalli-Sforza and Feldman, 1981)[14]. This paper provides evidence of a rapid change in cultural practices through the impacts of local media.

This paper contributes to the literature on health in developing countries (Dupas and Miguel, 2017). There is mixed evidence on the impact of information in shaping health behavior, ranging from no effect (Kremer and Miguel, 2007; Duflo et al., 2015), to an effect depending on the type of information provided (Dupas, 2011; Galiani et al., 2016). We highlight the role of broadcast information on the spread of disease. Given that health behavior is often tied to cultural norms, it is not surprising that the common knowledge aspect of providing this information through radio should be important.

This work also adds to the understanding of social and institutional factors of the spread of infectious diseases (Adda, 2016; Morse et al., 2016; Richards, 2016).

The paper is structured as follows. The following Section 3.2 gives a background on the spread of Ebola, the sources of social resistance behavior and a snapshot on the media outlook in Guinea and information campaigns during the Ebola outbreak. Section 3.3 gives a conceptual framework that borrows from the literature on global games and from epidemiological theory, with the intention to guide the empirical set-up and search for mechanisms. The empirical set-up and results are presented in Section 3.5. The main research design is presented in Section 3.5.1, where differences in radio signal reception

[14] An example of a very costly persistent practice is the case of the kuru virus. The deadly disease spread among the Fore people of New Guinea as a result of their tradition of eating the bodies of dead relatives and killed scores of the tribe members until the cause of illness was identified in 1950s and the cultural practice was discontinued. (Cavalli-Sforza and Feldman, 1981)

across Guinea and the timing of different radio campaigns are exploited to identify the effect of information campaigns transmitted through local radios on the spread of Ebola, as well as social resistance behavior and treatment uptake. Mechanisms are discussed in detail in Section 3.5.2. In Section 3.5.3 we provide robustness and validity checks for our main empirical strategy. We conclude in Section 3.6.

3.2 Background

This Section provides a background on the Ebola epidemic and response, the sources of distress and resistance behavior, as well as an overview of the media landscape in Guinea and information campaigns about Ebola[15].

The spread of Ebola

The Ebola virus disease (EVD) is a severe disease with a fatality rate varying from 25−90% at different stages of the outbreak. The virus is transmitted by physical contact with the blood, organs, secretions, or other body fluids of infected humans or animals, such as fruit bats or primates, as well as infected objects, such as needles and syringes. The disease is characterized by initial flu-like symptoms, which rapidly progress into vomiting, diarrhea, stomach pain and hemorrhage[16]. The incubation period, i.e. the time from infection with the virus to the onset of symptoms, is estimated at an average of 8-12 days in the 2014 Western African Ebola outbreak (Van Kerkhove et al., 2015), but it can potentially take up to 21 days. The virus can only be detected after symptoms arise, even in the laboratory, and it is hard to detect at early stages[17]. Infectiousness increases at later

[15] We provide a summary in Figure C.1

[16] `www.who.int/ebola` or `www.cdc.gov/vhf/ebola`

[17] "Diagnosing Ebola in a person who has been infected for only a few days may be complicated. The early symptoms of Ebola infection are difficult to distinguish from other, more common infectious diseases such as such as malaria, influenza, and typhoid fever. Ebola virus is detected in blood only after onset of symptoms, most notably fever, which accompany the rise in circulating virus, however, it may take up to 3 days after symptoms begin for the virus to reach detectable levels." from Centers for Disease Control and Prevention
`http://www.cdc.gov/vhf/ebola/healthcare-us/laboratories/specimens.html`

stages, with deceased bodies being the most contagious. Patients die within one or two weeks after onset of symptoms or recover becoming immune. Ebola survivors suffer with persistent medical conditions after recovery, including joint pain, loss of sight, headaches, and other chronic health issues, as well as social stigma.

Discovered in the 1970s, the Ebola virus has caused around twenty outbreaks to date, all in Africa, but this was its first time turning into an epidemic[18]. The 2014 West African Ebola epidemic is the largest in history, causing over over 28,600 infections and over 11,300 deaths, between December 2013 and April 2016[19]. Within less than a year the disease spread through Guinea, Liberia and Sierra Leone, small outbreaks reached Nigeria, Mali and a few cases were exported to Europe and the US. Halting an Ebola outbreak requires a great effort to treat symptomatic individuals, isolate infected people, trace their contacts, ensure safe burials and change population behaviors towards protective habits (Fast et al., 2014). This proved to be especially difficult in the present context of weak state capacity, slow international response, unfamiliarity with the disease and religious or cultural habits that facilitated its spread, especially through traditional burials and low treatment uptake.

Evidence suggests that the first index case[20] occurred in the Forest region in Guinea in December 2013 at the borders of Liberia and Sierra Leone. Subsequent cases spread exclusively through human-to-human contact. For eight to nine months these countries with very weak health systems and state capacity, tried to deal with the outbreak, with soaring death rates. Medecins Sans Frontieres (MSF), who scaled up their intervention, called it an 'unprecedented Ebola epidemic' already by end of March 2014. It was not until August 2014 that the World Health Organization (WHO) declared it an 'international public health emergency', followed by financial aid from international donors. By the time international aid reached the affected countries, over 4,000 cases had been confirmed. In-

[18]Definition of *epidemic* : affecting or tending to affect a disproportionately large number of individuals within a population, community, or region at the same time

[19]`http://www.who.int/csr/disease/ebola/en/`, accessed April 1, 2017.

[20]The first contagion to humans is zoonotic, i.e. entering in contact with a reservoir host, such as bats, for instance by eating rare bush meat.

ternational aid coordinated by the WHO implemented specialized medical infrastructure, contact tracing, surveillance systems and awareness raising campaigns. The peak of the outbreak due to the effectiveness of the interventions was reached by the end of 2014. The outbreak came to an end mid-2015, except for Guinea, which had a significant amount of cases until end of 2015. New infections still appeared in April 2016, but at that point new medical infrastructure and surveillance systems were in place to avoid another major outbreak and the epidemic was officially declared to an end in the summer of 2016.

Resistance behavior

Containment efforts were opposed by the civilian population either because they were coercive, such as forced detainment in Ebola treatment units (ETUs); the intentions of emergency assistance were misunderstood, through the spread of rumors; or they went against people's most fundamental beliefs, surrounding the burial of the deceased family members or taking care of the sick.

Ebola patients need to be isolated to avoid contagion and treatment requires special equipment[21]. This meant that patients could not be treated in hospitals and instead required the establishment of ad-hoc health centers, known as Ebola treatment units (ETUs)[22]. According to interviews conducted by the author with social workers in Guinea, the biggest source of rumors and conspiracy theories was around what was happening inside ETUs[23]. Given that Ebola was a new, unknown disease to the region, that early Ebola symptoms are very similar to other endemic diseases in the region and that people died in ETUs with a very high fatality rate at the beginning at the outbreak, it is not surprising that rumors spread[24].

[21]Including biohazard protection, such as the use of personal protective equipment (PPE) by doctors

[22]In some cases an alternative method emerged, known as Community care centers (CCCs), for first patient care of suspect patients. These were opened spontaneously by the communities and led by traditional caregivers, rather than professional staff.

[23]According to their accounts, an important way to halt the spread of rumors was for family members to come and see what was happening inside the ETUs.

[24]In pure observational probabilistic terms entering an ETU was a death sentence at the start of the outbreak, especially for patients that arrived when symptoms were already advanced.

The other major source of distress was the rapid change in cultural practices required to halt the spread of Ebola. Traditional burial practices involved washing the deceased by close family members. Since the Ebola virus is most infectious in dead bodies, changing this practice was a first priority. In Guinea the first attempt was to impose *safe burials*, which did not allow for traditional or religious customs. The personnel conducting the burials had to use personal protective equipment (PPE) to avoid their own contagion with the virus, which has a very impressive effect, as the whole body, including the face, is covered. In Guinea reported attacks against Red Cross volunteers, in charge of conducting these burials, averaged ten per month in the last six months of 2014[25]. *Safe burials* were progressively adapted to local customs, such as involving religious leaders, leading to what became known as *safe and dignified burials*.

Media landscape and information campaigns

Guinea ranks 101 in press freedom index with 33.11 points, classified as having a "noticeable problem", a classification shared with countries like Argentina, Brazil or Italy, better ranked than Belarus, Mexico or Russia, but worse ranked than Botswana, Romania or the United States[26]. There are four broad types of media outlets in Guinea: the international, the national, the private and the rural radio stations. Among the rural radios we also need to distinguish between having access to a radio station from your own community (prefecture) vs. receiving the signal from a rural radio based in another community. While the contents and signal strength are similar for each group (those individuals inside and those living outside the prefecture where the rural radio is located), the difference is that individuals with their own rural radio are listening to people from their own community, thus are more likely to trust them more, know them better or be more likely to understand their language. The international radio stations present in Guinea are the BBC, which is in English[27], and Radio France International, which did not con-

[25] IFRC, website.
[26] Reporters without Borders, `https://rsf.org/en/ranking`, accessed September 2017.
[27] Guinea is a French-speaking country

duct Ebola sensitization campaigns. The national radio stations are present throughout the country, but 18 out of 27 transmitters were not functioning for a long period, due to problems with energy access or other problems. There were 23 rural radio stations at the beginning of the period, and 11 new rural radios created at the peak of the epidemic. Of the old ones, 7 were repaired or received additional capacity in January 2015. While a large part of the whole country receives some signal from some rural radio station, there were only 23 out of 34 prefectures with their own community radio station until the peak of the outbreak[28]. Finally, there are 45 private radio stations, many of which overlap in the same area. Of these, 35 of them form a consortium called URTELGUI, pre-dating the epidemic, and that consortium aired Ebola programs.

There were four big broadcast information campaigns on Ebola. The first broadcast information campaign was conducted by the national radios, starting on April 7, 2014, four months after the first Ebola case, but less than a month after the official declaration of the Ebola outbreak in Guinea. This was aired over all national and gradually over all rural radios in the country as a synergy, which means that all people with access to that radio are listening to the program at the same time, hence making it difficult to avoid the information by changing channel. They were mostly reporting on cases in each location, prohibitions, measures taken and recommending the use of protective measures. While national radio stations emit programs in French, rural radio stations were adding complementary information in local languages. The program continued on a daily basis until the end of the outbreak.

The second broadcast information campaign started officially in the end of June 2014, coordinated by the directorate of the rural radios in the capital and diffused in local languages by the rural radios throughout the country. However, many of the rural radios started their own program on Ebola only later, some as late as end of September 2014[29]. The program improved over time, creating more persuasive content, including

[28]Within a prefecture, sub-prefectures have more or less access to it.

[29]To avoid endogenous using a start of the campaign that is endogenous to the spread of Ebola for each location, we base all our analysis on the official start of the rural radio campaigns, in June 2014.

Ebola survivors in their talk shows, as well as local, traditional or religious leaders, directly addressing rumors and giving locally relevant information in local languages. Some rural radios report adding new elements to their Ebola program as late as November 2014. The rural radios received significant help from the local branch of a non-governmental organization based in Switzerland, *Fondation Hirondelle*. They provided the rural radio stations with technical assistance and created contents in several local languages that the rural radio stations would directly upload in their programs. The first time this NGO shares contents with rural radio stations is in August 2014, although many rural radio stations incorporated their contents later on[30].

Thirdly, the private radio stations did not have a sustained program on Ebola sensitization, except for three synergies emitted by private radio stations that were part of the consortium URTELGUI. These were very short campaigns of a single day in April and July 2014 and a more prolonged one over several weeks in February 2015.

There was a fourth synergy starting in January 2015, "Ebola Chrono", conducted by the international organization Internews, which diffused throughout the national, rural and a set of private radio stations, three times per week. The contents were similar in spirit to the rural radio stations at their best time, but the intervention was a bit late in the timeline of the epidemic.

The main themes addressed in Ebola sensitization campaigns are summarized in Table 3.1.

Table 3.1: Main themes addressed in Ebola sensitization campaigns

First themes	Later incorporated
Ebola transmission	Addressing rumors about Ebola
Ebola prevention	Addressing resistance behavior
Ebola treatment	Stigmatization of Ebola victims

How did information change over time? The most significant change, according to a wide

We can think of it as an intention to treat estimate.

[30]See Supplementary Appendix Figure E.1 for a schedule of the Ebola sensitization campaign for two rural radios in Guinea.

variety of actors involved in the Ebola response and interviewed by the author in Guinea, was going from a factual description of the disease, that was contradictory and facilitated the spread of rumors, to more persuasive contents that addressed rumors and invited Ebola survivors and religious and local leaders in the radio shows. Instead of insisting on low risk habits that are hard to change, such as eating bush meat[31], the focus moved to high risk habits, such as burial practices and low treatment uptake. The type of messages aired at the beginning compared to after the messages were harmonized at national level are summarized in Table 3.2.

Table 3.2: Type of contents

First type of messages aired in radios (e.g. Gueckedou rural radio, March 26, 2014)
- "Ebola is a serious contagious disease, it can kill you. $60 - 90\%$ of people infected by the Ebola virus die."
- "We don't touch or transport dead bodies. We don't eat bush meat. We don't touch body liquids or secretions."

Sensitization campaign (gradually incorporated by rural radios after June, 2014)
- "Ebola is a deadly contagious disease but you can recover from it and take preventive measures of hygiene."
- "You can recover from Ebola if you go to an Ebola Treatment Unit early enough."
- "NGOs did not cause the spread of Ebola. They are helping defeat it."
- "We need to let the Red Cross conduct safe burials for us. They are protecting us."
- "People that survived Ebola do not have the Ebola virus. There is no reason to be scared of them. They should be respected."

[31] We have been eating bush meat for decades and never had Ebola. So they are obviously lying to us. Moreover, how can we substitute for it? (This was also a low risk habit, given that all contagions after the first case were human-to-human contagions, not zoonotic.).

3.3 Conceptual framework

This section gives a conceptual framework that borrows from the literature on global games and from epidemiological theory and closely follows Yanagizawa-Drott (2014). The purpose is to make explicit the different impact that we expect from information transmitted through radios, compared to other sources of information, on different types of health behavior. The aim of the information campaigns was on one hand to *inform* about the existence of the Ebola virus disease (EVD), its modes of transmission, prevention and treatment of the disease, and on the other, to *persuade* individuals to take preventive measures and treatment in case of contagion with the virus. The first objective is driven by the fact that Ebola is a new disease to the region and individuals have poor information about the actions that are needed to prevent and treat the disease. The second objective presumes that there is a trade-off in implementing the recommended behaviors. There are two main trade-offs in the context of a new epidemic. The first trade-off is that if the information is wrong, some of the recommended behaviors could harm one. This would be the case for instance, if rumors were correct in that people are killed in Ebola treatment units, or if the risks of eating bush meat are exaggerated[32] and hence decreasing its intake leads to unnecessary malnourishment. The other trade-off is that although the information is correct, taking the exhorted behaviors is costly. Some actions have private costs, such as washing hands with chlorine, in terms of time or incurring the price of chlorine. Other actions, such as safe burials, have social costs since changing burial practices violates a cultural norm.

We model the problem as a game of incomplete information, in which individuals' payoffs depend their own action, the action of others and the true state of the world. The proportion of individuals that take protective measures in equilibrium in turn affects the transmission rate of Ebola and hence the number of Ebola cases at each point in time. In this framework we can study how broadcast information affects behavior and ultimately

[32] As mentioned, only the first Ebola case was due to animal-to-human contagion, potentially through rare bush meat, but all other cases in the West African epidemic were human-to-human contagions.

the spread of the disease. We take a framework analogue to Yanagizawa-Drott (2014) based on the static global game structure developed by Carlsson and Van Damme (1993); Morris and Shin (1998, 2005).

Consider a continuum of individuals in a given location, here in a given sub-prefecture. Each individual can either refuse to take a protective action or abide by it. For instance, they can refuse a safe burial for their diseased family member, conducted by the Red cross, in order to have a traditional burial. If they refuse a safe burial they increase their own likelihood of contagion and incur a cost of θ but they obtain a social benefit of abiding with the social norm of $\alpha\, n$, where n is the proportion of individuals in their own community that refuse safe burials and $\alpha > 0$ captures the net benefit of following the norm[33]. In comparison, if they accept the safe burial, they obtain a baseline utility level normalized to 0. The utility of an individual is given by

$$u_i = \begin{cases} \theta + \alpha\, n & \text{if individual } i \text{ refuses protective measures} \\ 0 & \text{if individual } i \text{ accepts them} \end{cases} \tag{3.1}$$

Individuals will refuse protective measures if and only if doing so gives them a positive expected utility. There is incomplete information about the effect of protective measures on the likelihood of contagion, captured by the utility cost θ. This is where information comes in. Following the literature of global games, we assume that individuals have a diffuse prior on θ on the real line and they update their beliefs based on information they receive. On one hand, they receive an independent private signal, $x_i = \theta + \epsilon_i$, where ϵ_i is normally distributed with mean zero and variance σ_x^2. On the other, they receive a public signal, $p = \theta + \nu$, where ν is normally distributed with mean zero and variance σ_p^2.

Under this simple model we can cover the trade-offs described above. If the true state of the world is such that refusing protective measures increases the transmission rate, then $\theta < 0$. However, if the true state is that Ebola does not exist and people are

[33]The net social benefit is $\alpha = \alpha^N - \theta^N$ where α^N is the social benefit of conducting a traditional burial practice and θ^N is the cost of an increased transmission rate due to others conducting risky burial practices. Here we are considering the more interesting case $\alpha^N > \theta^N > 0$ which induces a trade-off in refusing safe burials in the true state of the world with $\theta > 0$.

killed in Ebola treatment units, then $\theta > 0$. Protective measures that are not observable by others, such as chlorine use, or for which there is no social norm, have no social cost, $\alpha = 0$. Protective measures with strong social norms attached have a social cost, inducing strategic complementarities in resistance behavior $\alpha > 0$. On the other hand, one can imagine some actions to be strategic substitutes, given externalities in health.

Individuals update their beliefs about θ using Bayes rule[34]. Consider the following switching strategy for individual i with or without radio $j = R, N$:

$$b(\overline{\theta_i^j}) = \begin{cases} 1 \quad refuse & \text{if } \overline{\theta_i^j} \geq \kappa^j \\ 0 \quad accept & \text{if } \overline{\theta_i^j} < \kappa^j \end{cases} \tag{3.2}$$

From Morris and Shin (1998, 2005) it follows that this is a unique equilibrium under some regularity conditions[35]. Therefore individuals whose posterior expectation of θ is above some equilibrium threshold κ^j engage in resistance behavior, while those below it do not. Yanagizawa-Drott (2014) shows that the equilibrium cutoff for individuals with radio depends on the fraction of other individuals receiving the radio signal r, $\kappa^R(r)$[36]. In our context, when the cost of refusing safe burials is *large* enough (i.e. θ very negative), the equilibrium number of people refusing safe burials *decreases* with the fraction of people that have access to the radio[37]. There are two main predictions that are relevant here. First, without strategic complementarities, $\alpha = 0$, the individual decision is not affected by others' decision and one can show that the number of people refusing burials decreases linearly in the number of people exposed to the radio signal. In this case the radio provides

[34]For individuals receiving only the private signal, the posterior distribution of θ has mean x_i and variance σ_x^2. For those receiving the radio signal also, the posterior distribution of θ has mean $\frac{\sigma_x^2\, p+\sigma_p^2\, x_i}{\sigma_p^2+\sigma_x^2}$ and variance $\frac{\sigma_x^2\, \sigma_p^2}{\sigma_x^2+\sigma_p^2}$.

[35]Proofs are identical to Yanagizawa-Drott (2014).

[36]In particular, for individuals without radio, $j = N$, the equilibrium cutoff is $\kappa^N = -\alpha/2$. For individuals with radio $j = R$, the equilibrium condition is given by $\kappa^R + \alpha[r\Phi(\frac{\sigma_x^2(p-\kappa^R)}{\sigma_p^2\gamma}) + (1-r)\Phi(\frac{\alpha/2+\kappa^R}{\gamma})] = 0$ where r is the fraction of individuals with access to the public signal, Φ is the standard normal CDF and $\gamma = \sqrt{\frac{2\sigma_x^2\sigma_p^2+\sigma_x^4}{\sigma_x^2+\sigma_p^2}}$.

[37]A sufficient condition for $\frac{\partial n}{\partial r} < 0$ is that $p < -\alpha/2$. Proofs are similar to Yanagizawa-Drott (2014) and are therefore omitted here.

a pure *information effect*, but there is little additional benefit given by the public signal, compared to the private signal. Secondly, with strategic complementarities, $\alpha > 0$, the individual decision to refuse a safe burial is increasing in others' decision to do so and hence there are increasing scale effects of broadcast information, so that $\frac{\partial^2 n}{\partial^2 r} \leq 0$. This is the *coordination effect* due to the common knowledge aspect of the radio signal, as individuals know the proportion of other individuals that have learned about the new state of the world and hence have an expectation of the fraction of individuals that will refuse burials.

In this setting we can think of r as the fraction of people that have actually listened to the information via radio. If not everybody listens to the radio every day, r is a function of the share of a sub-prefecture that has access to a given radio and the months of exposure. In this case we expect the effect of the radio campaigns to take time to affect behavior.

When comparing different information campaigns we think of ranking them in the precision of their signal. A local media outlet is more accurate than a media outlet from a distant community or from the national media outlet (smaller σ_p) in that it explains better the concrete ways in which individuals in a given community are putting themselves at risk of transmission[38].

Finally, the equilibrium number of individuals that take protective measures affects the transmission rate of Ebola at each point in time. The epidemiological theory applied to the Ebola virus disease (EVD) suggests that new Ebola infections $y_{d,t}$ in each sub-prefecture d at time t follow exponential growth with transmission rate $\beta_{d,t}$ on a fraction $\rho \in [0, 1]$ of past cases (Lekone and Finkenstädt, 2006; Fang et al., 2016). This literature models the effect of information transmission on the transmission rate $\beta_{d,t}$ (Funk et al., 2009; Kiss et al., 2010). We therefore consider the following model of exponential growth

[38]If a media outlet is biased, for instance because it exaggerates the benefits of taking protective measures, the error term ν has a mean $\nu_p < 0$. In this case listeners would adjust for the bias when they update their beliefs about θ.

of Ebola infections:

$$y_{d,t} = y_{d,t-1}^{\rho} \; e^{f(\beta_0, b(r_{d,t}), X_{d,t})} \tag{3.3}$$

Where the transmission rate $\beta_{d,t} = f(\beta_0, b(r_{d,t}), X_{d,t})$ is a function of baseline transmission rate β_0, the equilibrium strategies $b(r_{d,t})$ and baseline covariates $X_{d,t}$. As described above, the equilibrium strategies depend on the radio signal $r_{d,t}$, which we measure as the interaction between radio signal exposure $RadioSignal^d$, pre-determined at sub-prefecture level, and the timing τ_k in which a particular radio campaign k was launched throughout the country:

$$r_{d,t} = \begin{cases} 0 & \text{if } t < \tau_k \\ RadioSignal^d & \text{if } t \geq \tau_k \end{cases} \tag{3.4}$$

We further simplify the model above by approximating the transmission rate $\beta_{d,t}$ with a linear function $\beta_0 + \beta_1 \; r_{d,t} + \beta_2 \; X_{d,t}$ and taking logs in (3.3):

$$\ln(y_{d,t}) = \rho \; ln(y_{d,t-1}) + \beta_0 + \beta_1 \; r_{d,t} + \beta_2 \; X_{d,t} + \epsilon_{d,t} \tag{3.5}$$

where $\epsilon_{d,t}$ captures the probability that new cases are generated from contagion with distant communities or animal-to-human transmission. Equation (3.5) guides the main empirical strategy.

3.4 Data

Radio data

The treatment variable of interest is the share of a sub-prefecture that has access to a given radio interacted with the timing of the start of an information campaign about Ebola. The radio signal reception measure is constructed in several steps for each type of media outlet: rural, national, private and international radios. First, the radio signal is constructed using a radio propagation tool used by radio and TV engineers, based on the Irregular Terrain Model (ITM) / Longley-Rice, standard in the economics literature since Olken (2009). The signal is calculated for each of a total of 155 transmitters, based on geographic terrain features, transmitter location and technical characteristics collected from the National Telecommunications Agency in Guinea (ARPT). Second, we group radio transmitters by type of media outlet[39]. The areas covered by each type of media outlet are shown in Figure 3.1. Third, using the union of radio signals for a given media outlet, we calculate the share of a given sub-prefecture that has access to it[40].

The main treatment variable of interest is the share of a sub-prefecture that has access to a rural radio from their own community (i.e. prefecture) with a signal strength of at least 43 $dB\mu V/m$[41]. Figure 3.1 shows the radio signal coverage for any rural radio in Guinea. The radio signal coverage for their own rural radio is shown in form of descriptive statistics in Table 3.3[42]. This Table shows that most sub-prefectures have at least half of their territory covered with at least one media outlet. The most common media outlet are the rural radios, followed by the national radios. However having access to a rural radio station from their own community is less common. The median (mean) share of a sub-prefecture with an own rural radio is 14% (28%). The least common media outlet are private radios.

The timing and contents of the information campaigns about Ebola by different media outlets were collected by the author during in-person interviews with the director of the national radio and television, the director of the rural radios[43], the director of the private-radio consortium, as well as the main private radios, and via phone-interviews and surveys

[39] Any rural radio, rural radios given pre-epidemic, new rural radios constructed at the end of the epidemic, national radios, national radios that work, national radios with broken transmitters, private radio stations, private radio stations in the URTELGUI consortium and those that are not, international radio stations.

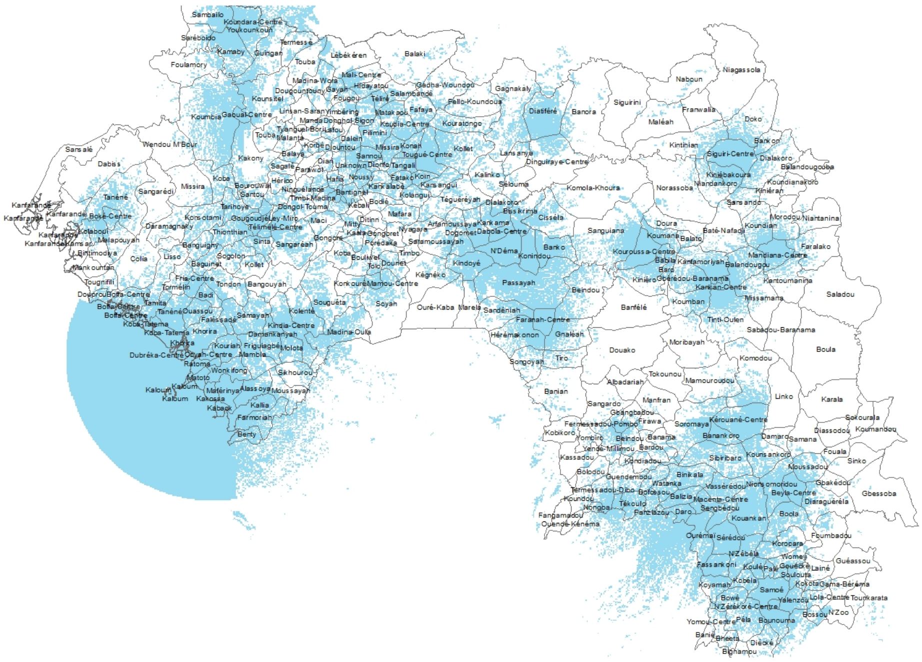
[40] The procedure is illustrated in Figure C.2

[41] The reception is measured in field strength $dB\mu V/m$, where the signal is deemed as sufficient under normal circumstances if it is at least $43dB\mu V/m$. The software calculates two signal reception measures, one based on this threshold and one based in a lower threshold, $33dB\mu V/m$. We use the higher threshold, as it is considered more relevant for normal receivers.

[42] Given a signal strength of at least 43 $dB\mu V/m$.

[43] Direction des Radios Rurales de Guineé

Figure 3.1: Radio signal reception to any Rural radio



Notes: With a signal strength of at least 43 $dB\mu V/m$

via email to all rural radio stations and the most relevant private radio stations in Guinea.

Ownership of radio devices, radio listening patterns and baseline covariates are taken from three sources. Firstly, we use household survey data from the Afrobarometer, namely Round 5 (2013) of 1,310 individuals. We also show complementary evidence of the radio signal measure being correlated with radio ownership and listening patterns in Round 6 (2015) with 1,200 individuals. In each case survey weights are used to aggregate at the level of sub-prefecture. Secondly, we use a household survey on impacts, beliefs and knowledge about Ebola from a representative post-Ebola survey conducted by the Guinean National Institute of Statistics (INS) of 2,466 people. Survey weights are used to aggregate covariates at the level of a sub-prefecture. Finally, we give complementary evidence using a phone-survey of 1,000 individuals conducted by Internews, an international Organization that conducted the last widely-aired Ebola program, "Ebola Chrono"[44].

[44]Evidence based on this survey is interpreted only as suggestive, given that it is not representative and in addition most individuals are surveyed in the main sub-prefecture within each prefecture, a total of 35 sub-prefectures.

Table 3.3: Share of Sub-prefecture covered by each Radio signal (fair signal)
With a radio signal strength of at least 43 $dB\mu V/m$

	median	mean	sd	min	max
Any Radio	0.63	0.59	0.32	0.00	1.00
Any Radio (incl. broken)	0.69	0.63	0.32	0.00	1.00
National	0.18	0.29	0.31	0.00	1.00
National (incl. broken)	0.38	0.42	0.32	0.00	1.00
Private	0.06	0.23	0.32	0.00	1.00
Private-Urtelgui	0.03	0.20	0.30	0.00	1.00
International	0.01	0.16	0.28	0.00	1.00
Any Rural Radio	0.42	0.47	0.32	0.00	1.00
Own Rural	0.14	0.28	0.32	0.00	1.00
Observations	341				

Notes: Some transmitters are not working during the time of the outbreak, those are referred here as broken transmitters.

Epidemic data

The main outcome of interest is the number of Ebola infections, taken from patient records from the World Health Organization (WHO) in Guinea. Ebola cases can be either probable or confirmed, depending on the stage at which patients have been identified, based on symptoms or laboratory testing. Infections are reported at weekly level and the date corresponds to the actual or estimated date of symptom onset. Hence, these are contagions that necessarily occurred prior to the week of report, most likely in a time window of 1-2 weeks before. We aggregate the data at monthly level since we are interested in the effects of information on the overall spread of the disease and we hypothesize that information will take time to affect behavior and hence new contagions. This also allows us to take into account the possible time-span from contagion to symptom onset (2 weeks) and allow for additional 2-3 weeks, thus reducing the possibility of measurement error in the timing of contagion. Cases are recorded at the level of sub-prefecture. Our main measure of infections are the log number of Ebola infections +0.01 in a sub-prefecture over a month from January 2014 to May 2016 (341 $\times$ 29 observations).

Social unrest or resistance behavior[45] was scraped from Situation Reports (daily or weekly),

[45] The term used in the Ebola outrbeak was *resistance* in English and *reticence* in French.

which were conducted by the Guinean Ministry of Health, using simple data-scraping algorithms. Figure C.3 shows one example of a Situation Report recording resistance data. The data is aggregated at sub-prefecture and weekly level and takes values 1 if one or more resistance behaviors were recorded in a given week and 0 otherwise. The dichotomous variable at the weekly level allows us to reduce measurement error due to some Situation Reports giving more or less geographically dis-aggregated information. We then aggregate this measure at the monthly level, thus measuring the number of weeks with resistance behavior in a given month for each sub-prefecture.

Another outcome used is the number of people that die from Ebola in their own community divided by the total number of individuals that die from Ebola, including those that die in a treatment center. This gives us a measure of resistance to protective measures or treatment uptake, suggested by the WHO in Guinea, who provided this data. Similarly, we study the evolution of refusals to conduct safe and dignified burials (SDB) over the total number of SDBs conducted by the Guinean Red Cross. This data comes from the International Federation for the Red Cross and Crescent Movement in Guinea (IFRC). The data is only available at prefecture $\times$ week from April to December 2015. We aggregate it at monthly level (34×9 observations). Summary statistics for the main outcome variables are shown in Table 3.4[46].

Other data

The location of laboratories and health treatment units, such as Community care centers (CCCs) and Ebola Treatment Units (ETUs) are from the WHO and the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA). Population data is taken from the 2014 census in Guinea. Village location or population, roads and other

[46]For aggregate statistics see Table C.1. Summary statistics for the main outcome variable by access to local radios, conditional on access to rural radios, are shown in Supplementary Appendix Table E.1. They show a higher level of Ebola, as well as a higher ratio of deaths in community compared to deaths in ETU and more refusal of safe burials.

Table 3.4: Summary Statistics - Outcome variables

	mean	sd	min	max	count
Ebola cases	0.39	3.11	0.00	100.00	9889
Ebola cases per capita in 100k	1.14	10.76	0.00	513.11	9889
Log Ebola+0,01	-4.31	1.33	-4.61	4.61	9889
Resistance behavior	0.07	0.42	0.00	5.00	9889
Ebola total deaths	0.26	2.15	0.00	77.00	9889
Ebola deaths in community	0.11	0.98	0.00	47.00	9889
Ebola deaths in ETU	0.15	1.36	0.00	57.00	9889
Community over ETU deaths ×100	1.48	8.65	0.00	88.89	9889
Sub-Pref × Month from 1.2014-5.2016					
Refused burials	0.10	0.65	0.00	8.00	986
Refused burials in 100k per cap.	0.04	0.23	0.00	3.11	986
Pref × Month from from 4.2015-12.2015					

geographic data are from l'Observatoire National des Ressources de la Guinee, ONRG. Prevalence of other diseases is available at prefecture level for 2013 and 2014, from the Guinean Ministry of Health. Finally, we also use data on the number of radio emissions and social mobilization campaigns conducted by the International Federation for the Red Cross and Crescent Movement in Guinea (IFRC). The data is only available at prefecture × week from April to December 2015. We aggregate it at monthly level (34 × 9 observations). Summary statistics for the main covariates are shown in Table 3.5.

3.5 Empirical Strategy

The core of this paper lies on identifying the impact of broadcast information on the spread of Ebola. In addition we use a number of strategies to support our hypothesis that the way in which information affects the spread of the disease is through a change in behavior, in particular preventive measures that are observable, such as treatment uptake and burial practices.

The main research design is presented in Section 3.5.1, where differences in radio signal

Table 3.5: Summary Statistics - Covariates

	mean	sd	min	max	count
Number of ETUs	0.08	0.58	0.00	5.00	9889
Number of Labs	0.08	0.58	0.00	5.00	9889
Number of CCCs	0.69	1.60	0.00	5.00	9889
Log-Distance to ETU	11.33	1.95	0.00	13.32	9744
Log-Distance to Lab	11.21	2.03	0.00	12.81	7982
Log-Distance to CCC	8.38	3.78	0.00	11.58	9744
Sub-Pref × Month from 1.2014-5.2016					
Total burials	22.27	138.74	0.00	1747.00	986
Red Cross Radio Emissions	0.26	1.87	0.00	29.00	986
Social Mobilis. Response	867.08	3961.57	0.00	41144.00	986
Social Mobilis. Preventive	170.22	1025.98	0.00	12343.00	986
Pref × Month from from 4.2015-12.2015					
Population	33119.28	66387.91	6495.00	682610.00	341
Log-Population density	429.91	1043.19	33.73	12310.35	341
Log-Distance to epicenter	12.37	0.72	10.01	13.17	341
Sub-Prefecture in 2014					

reception across Guinea and the timing of different radio campaigns are exploited to identify the effect of information campaigns transmitted through local radios on the spread of Ebola, as well as social resistance behavior and treatment uptake. Section 3.5.3 provides a number of validity checks to asses the validity of the design.

Mechanisms are discussed in detail in Section 3.5.2. Firstly, we provide evidence that our measure of radio signal reception is correlated with ownership of radio devices and radio listening patterns, Section 3.5.2. Secondly, we use survey data on post-Ebola beliefs and stated behavior to assess whether listening to an Ebola program on the media is related to greater knowledge about the disease and treatment uptake, Section 3.5.2. Thirdly, we exploit data from the Red Cross on weekly radio emissions, social mobilization campaigns, safe burials and refused burials to study whether radio emissions are followed by a change in burial practices. Finally, we discuss the role of local information in affecting beliefs and behavior change in Section 3.5.2.

3.5.1 Local radios and the spread of Ebola

The aim of this paper is to identify the impact of broadcast information on social unrest or resistance behavior and on the spread of Ebola. The main empirical strategy follows the same logic as a standard difference-in-difference strategy with continuous treatment. We compare areas with varying access to distinct media outlets that pre-date the start of the epidemic, before and after a given information campaign starts several months after the beginning of the Ebola outbreak. More precisely we study the effect of having access to an information campaign aired in a local radio on the spread of Ebola and resistance behavior. Identification relies on a parallel trends assumption, namely that areas with greater access to a local radio would have behaved similarly to other areas in the absence of the information campaign.

The design is similar to previous literature on media that uses features of the geographic terrain and pre-existing exposure to radio signal reception to identify the effect of broadcast information on a relevant economic outcome (Olken, 2009; La Ferrara et al., 2012; Yanagizawa-Drott, 2014; DellaVigna et al., 2014; Adena et al., 2015), but it adds two additional dimensions that strengthen the design. Firstly, we add a time dimension, since we observe the Ebola outbreak for at least six months before the rural radio campaign starts. Secondly, we add a control group, namely areas that have access to information from other radio stations, or areas that have access to the same information campaign from other rural radio stations.

First we conduct a simple difference-in-difference exercise summarized in equation (3.6).

$$\begin{aligned} Outcome_{d,t} = {} & \beta \, Radio_d^{Local} \times PostCampaign_{\,t} + \sum_{k \neq Local} \gamma^k \, Radio_d^k \times PostCampaign_{\,t} \\ & + \mathbf{X}_{d,t} \, \Gamma + \alpha_d + \lambda_t + \epsilon_{d,t} \end{aligned} \tag{3.6}$$

The treatment of interest is the interaction between the radio signal reception for a local rural radio station $Radio_d^{Local}$ in sub-prefecture d and the post-treatment dummy specifying the start of the rural radio campaign $PostCampaign_t$ in month t. This interaction corresponds to $r_{d,t}$ in the theoretical model above, Section 3.3. We control for access to other radio stations interacted with the post-treatment dummy. In particular we control for access to any radio station, to any rural radio station, to private and to national radio stations[47]. Hence the coefficient of interest, β, measures the overall marginal impact of the rural radio campaign aired by local radio stations on a given outcome, conditional on the access to other radios and other controls.

The main outcome of interest is the spread of Ebola. In particular we use the log of Ebola cases as dependent variable, motivated by equation (3.5) in the theoretical model[48]. To avoid the inclusion of a lagged dependent variable we assume that past Ebola cases will be largely captured by location fixed effects α_d and time fixed effects λ_t. Given that we are dealing with one single epidemic outbreak, the assumption seams reasonable. However for robustness we also run an alternative specification with a lagged dependent variable instead of the fixed effects, which gives us a lower bound estimate of the true effect (Angrist and Pischke, 2008). Other outcomes studied are the number of weeks with resistance events in a given month for a given sub-prefecture[49] and the ratio of people that die from Ebola in their community over the total deaths from Ebola[50]. We also run the same regression equation for these outcomes adjusted by population in 100'000[51].

$X_{d,t}$ is a set of time-varying or time-invariant controls interacted with the post-treatment dummy, $Z_d \times PostCampaign_t$. This includes the distance to the closest radio transmitter to each media outlet, $\sum_k DistanceToTransmitter_d^k$, which serves as proxy for the free space signal, i.e. the radio signal in absence of geographical accidents. This should address

[47]These are radios that pre-date the spread of Ebola and that are currently working (no broken transmitters).

[48]Our preferred specification is $log(Ebola + 0.01)$, as this allows us to interpret the coefficient β^{Local} directly as the % change in the number of Ebola cases as a result of a 1 *pp.* increase in the access to a local radio. Results are consistent when using alternative specifications, such as $log(Ebola + 1)$.

[49]We first record whether there was any such event in a given week (to reduce possible measurement error in the number of events reported in the daily/weekly Situation reports) and then we aggregate such events per month.

[50]We use the ratio *(Ebola deaths in community / 1+ Total Ebola deaths)* $\times$ *100*

[51]Where $log(ebola + 1)$ stands for $log(Ebola/population \times 100'000 + 1)$

the potential concern that areas with a local radio signal are fundamentally different from other areas due to their proximity to the radio tower. We also control for population, population density, geographic area, distance to the epicenter or first Ebola case, as well as proxies for wealth and education, interacted with the post-treatment dummy. We include the shortest distance to an Ebola Treatment Unit (ETU), laboratory and community care center (CCCs) at each point in time. Standard errors are clustered at prefecture × year to account for spatial and serial dependence.

The main empirical strategy is a fully flexible difference-in-difference strategy allowing for the effect to change over time, summarized in equation (3.7).

$$\begin{aligned} Outcome_{d,t} = \beta_j \; Radio_d^{Local} \times \mathbb{1}_t(j)^{Campaign} + \sum_{k \neq Local} \gamma_j^k \; Radio_d^k \times \mathbb{1}_t(j)^{Campaign} \\ + \mathbf{X}_{d,t}\,\Gamma + \alpha_d + \lambda_t + \epsilon_{d,t} \end{aligned} \tag{3.7}$$

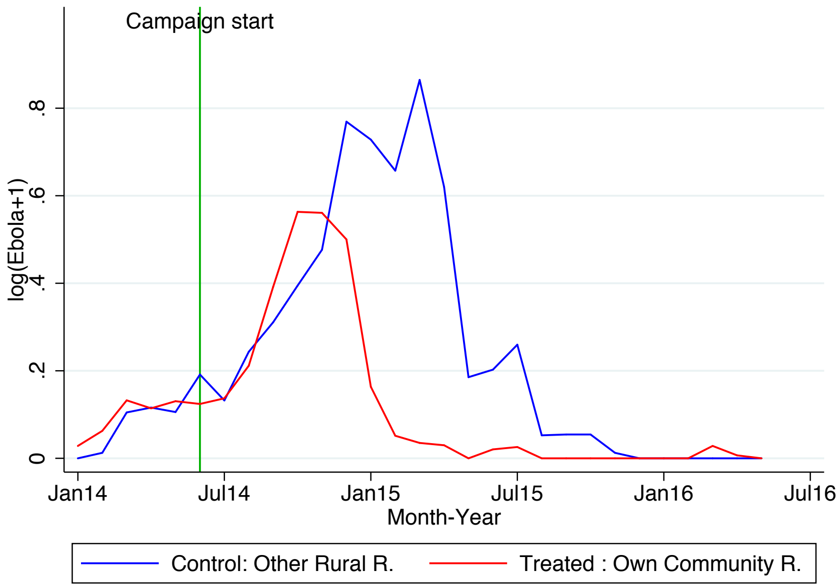
Everything is identical to the standard difference-in-difference equation (3.6) but instead of the post-treatment dummy $PostCampaign_t$ we use time dummies $\mathbb{1}_t(j)^{Rural}$, for j periods before/after the start of the rural radio campaign[52]. The coefficients of interest are $\{\beta_j\}_{j \geq 0}$, which measure the marginal impact of the rural radio campaign aired by local radio stations on the spread of Ebola, after j periods, conditional on covariates and on the access to other radios. This specification allows us to plot each of the coefficients β_j and test the parallel trends assumption, i.e. $\beta_j = 0$ for all $j < 0$. Finally if information takes time before it is absorbed and translates into preventive behavior, which eventually lowers the spread of Ebola, we expect $\beta_j = 0$ for some $j \geq 0$ and $\beta_j < 0$ only after several periods.

[52]The omitted category is $j = -1$, the period immediately following the start of the campaign. We start at -5, which is our first observed month, January 2014.

Results on the effect of Local radios on the spread of Ebola

The main result of this paper is summarized in Figure 3.2. It plots the average log-Ebola cases for sub-prefectures with above and below median access to a local rural radio station, conditioning on sub-prefectures with above mean access to some rural radio station. It shows that areas with access to rural radios of their own community had a similar evolution in the spread of Ebola, compared to areas with other rural radios, during the first six months of the outbreak prior to the start of the rural radio campaign, a rise thereafter, and an abrupt drop in cases approximately three months earlier than other areas. The Figure also motivates the validity of the design. Not only do we have parallel trends but also the same level of log-Ebola prior to the start of the rural radio campaign[53].

Figure 3.2: Log-Ebola in areas with above/below median access to
Own Community Rural Radio signal



Notes: The outcome is $log(Ebola + 1)$, where $Ebola$ is the number of Ebola cases.
We show a similar plot for $log(Ebola + 0.01)$ in Figure C.4.
The Figure plots the average log-Ebola for sub-prefectures with above and below median access to a local rural radio station, conditioning on sub-prefectures with above mean access to some rural radio station.

The results to our main specification are shown graphically in Figure 3.3. First, we see

[53]Figure C.4 shows that the pattern is similar if we define log-Ebola as $log(Ebola + 0.01)$ instead of $log(Ebola + 1)$.

that the parallel trends assumption is satisfied in our regression framework. There is no difference in the spread of Ebola for areas with varying levels of access to an own rural radio, controlling for access to other radios, prior to the start of the campaign, i.e. $\hat{\beta}_j = 0$ for all $j < 0$. This holds also conditional on a number of other controls correlated with the spread of disease. Secondly, it shows that the impacts of the campaign were not immediate, that is, the transmission rate of Ebola cases dropped in areas with access to local radios seven months after the first time rural radios started a sustained campaign encouraging protective measures, addressing Ebola rumors and new burial practices, and that increasingly incorporated local, traditional or religious leaders and Ebola survivors into its programming. This pattern is also evident in the evolution of resistance behavior, measured as violence or resistance against authorities, medical teams, social workers, refusal of safe burials or treatment uptake. We also see a gradual drop in the ratio of Ebola deaths in community compared to total Ebola deaths, including those who died in an ETU. This gives us a measure of treatment uptake.

The regression output is shown in Tables C.2-C.4. A 10 percentage point (*pp*) increase in access to a local radio[54] lowers the number of Ebola cases by $13 - 18\%$ each month after the seventh month following the start of the campaign[55]. This holds conditional access to other radios, distances to the closest radio transmitter for each media outlet, demographic controls, population, population density and distance to the epicenter, interacted with the time dummies, as well as the time-varying distance to the closest ETU/laboratory/CCC at each point in time.

There is a contemporaneous drop in resistance in the same month as the drop in the transmission rate of Ebola, Table C.3, possibly suggesting that some of this resistance behavior is a response to Ebola, rather than a mechanism. However, we also see weak evidence of a much more gradual and earlier drop in resistance behavior, compared to

[54] This interpretation makes more sense since our treatment variable, radio signal, is a share in $[0, 1]$.

[55] The coefficients in Table C.2 can be read directly as the percentage change in the number of Ebola cases due to a 1 *pp* increase access to a local radio, or the coefficients $\times 10$ as the approximate effect of a 10 *pp* increase in access to a local radio.

the transmission rate, going from a suggestive drop by 10% in the fourth month, to a statistically significant drop by 34% in the seventh month, which stabilizes at 13% thereafter, for a 10 *pp* increase in access to a local radio[56]. Similarly, there is a gradual decrease in the relative number of Ebola deaths in community[57], by a suggestive 25% in the seventh month and a statistically significant drop by 41% in the eighth month as access to a local radio increases by 10 *pp*, Table C.4[58].

The results of the difference-in-difference strategy specified in equation (3.6) are smaller and less precisely estimated, but they show a similar pattern. As access to local radios increases by 10 *pp*, the number of Ebola cases drops by approximately $4-5\%$ and the number of Ebola cases in 100'000 per capita drops by $3-5\%$ over the following months, Table C.5[59]. For consistency we also test that there is no linear trend in log-Ebola, prior to the start of the campaign[60].

Together this evidence suggests that while broadcast information by local radios took time to be absorbed, it eventually led to a drop in social resistance behavior, an increase in treatment uptake and eventually helped halt the Ebola epidemic.

We can do back-of-the-envelope calculations to understand how many Ebola cases would have been spared with greater access to local radios. For instance comparing areas above and below median access to local radios, conditional on above median access to rural radios, we are comparing areas that have on average 76% access to a rural radio but no access to one from their own prefecture, vs. areas that have 74% access to any rural radio and 65% access to one from their own community. The total number of Ebola cases

[56]We see weak evidence of a rise in resistance in the fourth month after the start of the campaign, but the effect is only a 8% rise in resistance and it is no longer there when we look at resistance in 100'000 per capita, Table E.8. In this case resistance in 100'000 per capita drops by 51% in the seventh month for a 10 *pp* increase in access to a local radio.

[57]Percentage of Ebola deaths in community over total deaths + 1, where total deaths include Ebola deaths in community and deaths in a ETU.

[58]We are excluding Gueckedou, first prefecture to be hit by Ebola, in order to study a sample with similar ratios of deaths in community vs ETU prior to the start of the rural information campaign. See Supplementary Appendix Figure E.3 for results with the full sample.

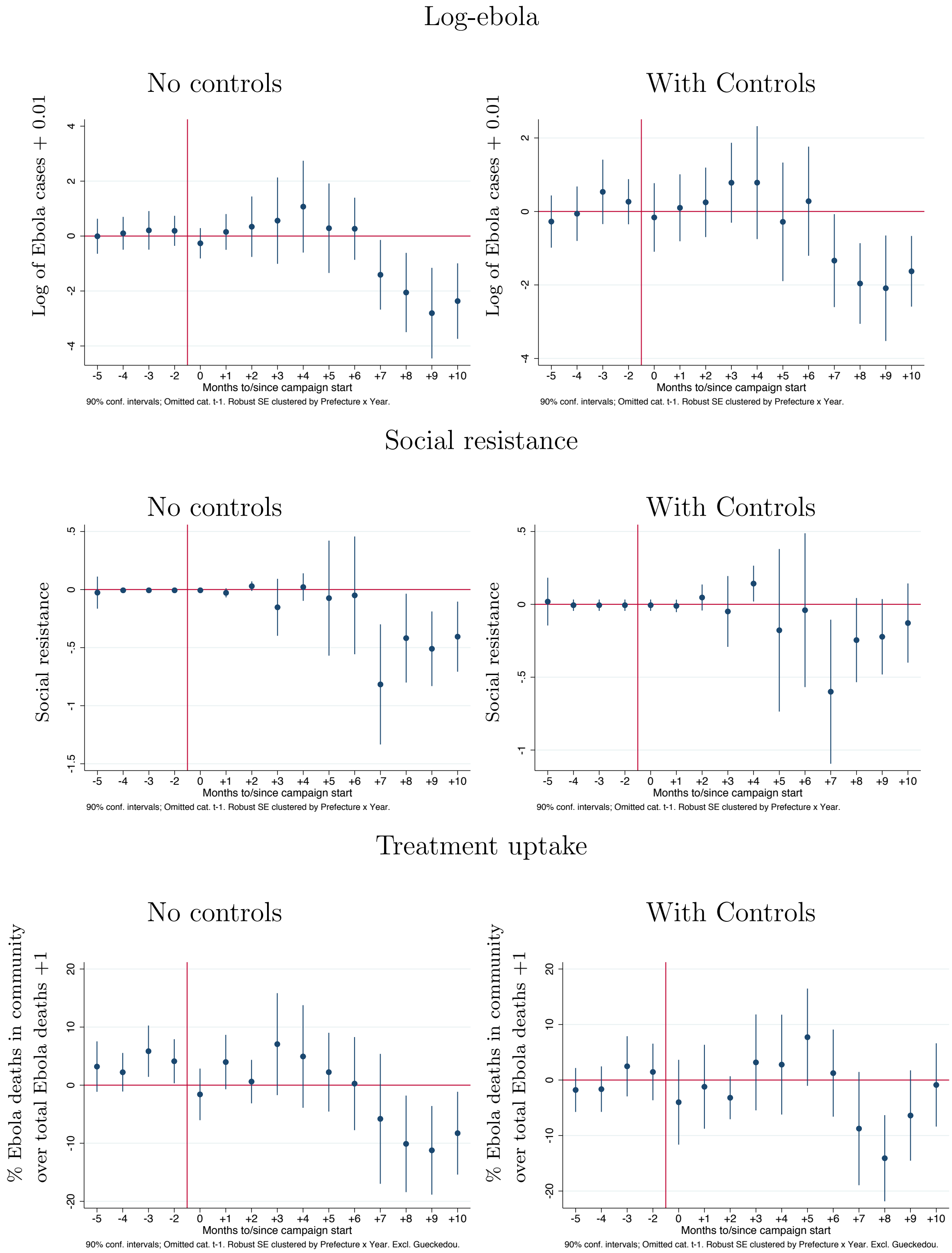
[59]The results are more precisely estimated when we exclude Gueckedou, the prefecture first hit by Ebola, but they are similar in magnitude when we include it, Supplementary Appendix Table E.11.

[60]Supplementary Appendix Table E.9

in those areas without an own community radio is 1560 over the entire epidemic and 1446 in the post-rural campaign period[61]. Our difference-in-difference results mean that an increase by 65 *pp* in access to a local radio would have meant 21% less Ebola cases. This means that 303 Ebola cases occurring in the post-July 2014 period would have been spared, that is 8% of the total number of Ebola cases.

[61] That is, after July 2014. See Supplementary Appendix Table E.2

Figure 3.3: Event studies
Pre/Post Rural campaign by access to Own Community Rural Radio signals



Notes: 90% confidence intervals. Robust Standard Errors clustered by Prefecture × Year. Last Figures exclude Gueckedou Prefecture. For alternative specifications see Figures E.2-E.3.
Controls: wealth level, education, rural, population, population^2, population-density; log-distance to epicenter, to the closest radio transmitter from any radio, national, private, rural, own rural radio (working and pre-existing), to the closest ETU, CCC and laboratory at each time × time-dummies.

3.5.2 Mechanisms

In this Section we give a number of strategies that are intended as suggestive evidence of mechanisms underlying the main empirical findings described above. Firstly, we provide evidence that our measure of radio signal reception is correlated with ownership of radio devices and radio listening patterns, Section 3.5.2. Secondly, we use survey data on post-Ebola beliefs and stated behavior to assess whether listening to an Ebola program on the media is related to greater knowledge about the disease and treatment uptake, Section 3.5.2. We also use our radio signal measure as instrument for hearing about Ebola on the media. Thirdly, we exploit data from the Red Cross on weekly radio emissions, social mobilization campaigns, safe burials and refused burials to study whether radio emissions are followed by a change in burial practices. Finally, we discuss the role of local information in affecting beliefs and behavior change in Section 3.5.2. In particular we rule out a supply-side channel of political accountability and we discuss the role of language, ethnic belonging and trust in local institutions in explaining the importance of local radios.

Information uptake

The first exercise is to asses whether the radio signal measure constructed predicts radio listening patterns. We present here evidence using survey data from three sources, Afrobarometers Rounds 5 (2013) and 6 (2015), of 1,310 and 1,200 individuals, respectively; a post-Ebola survey by the Guinean National Institute of Statistics (INS) of 2,466 people and a phone-survey of 1,000 individuals conducted by Internews, an international organization that created the last widely-aired Ebola program, “Ebola Chrono”.

In a simple OLS design, we explore whether people who have access to any radio signal, according to our constructed measure, own more radio devices or listen more to news on the radio and whether there is a difference for a given media outlet d, equation (3.8). We also study whether people with higher access to a particular radio signal k are more likely to listen to that media outlet k, either to the general program, or to a program about Ebola on that radio, equation (3.9). Using self-reported measures we assess whether individuals who report listening to a given radio k, are more likely to listen to an Ebola program aired on the radio (3.10). We then conduct this last exercise using access to a particular radio signal k, instead of self-reported listening patterns (3.11).

$$OwnRadioDevice_i = \alpha_0 + \alpha_1\ AnyRadioSignal_d + \alpha_2\ RadioSignal_d^k + \epsilon_d \tag{3.8}$$

$$ListenRadio_i^k = \beta_0 + \beta_1\ RadioSignal_d^k + \mathbf{X}_i\ \Gamma^\beta + \epsilon_d \tag{3.9}$$

$$ListenEbolaProgram_i = \gamma_0 + \gamma_1\ ListenRadio_i^k + \mathbf{X}_i\ \Gamma^\gamma + \epsilon_d \tag{3.10}$$

$$ListenEbolaProgram_i = \delta_0 + \delta_1\ RadioSignal_d^k + \mathbf{X}_i\ \Gamma^\delta + \epsilon_d \tag{3.11}$$

Standard errors are clustered at the level of sub-prefecture, since this is the level of observation of our radio signal measure. We add individual-level controls, namely a wealth index and an education variable, as well as population and population density.

Results to Information uptake

Individuals in areas with higher access to any radio signal own more radio devices and listen more to news on the radio, Table 3.6. An increase by 10 percentage points in access to any radio signal is associated with a $2 - 5\%$ increase in the ownership of radio devices and a $2,5 - 6\%$ increase in the number of times they listen to news on the radio. There is also weak evidence that these areas are more urban. When split across different media outlets, there are weak differences - people in areas with higher access to an own rural radio or to private radio stations have higher ownership of radios[62].

We also find evidence from the GeoPoll survey conducted by Internews that our measure of radio signal is predictive of people listening to that particular media outlet[63].

[62]Supplementary Appendix Table E.15
[63]Supplementary Appendix Tables E.16-E.18

Table 3.6: In areas with higher access to a radio signal (from any radio), more people own radio devices and listen to news on the radio

	Owns Radio		News-Radio		Urban	
	(1)	(2)	(3)	(4)	(5)	(6)
	R5	R6	R5	R6	R5	R6
Any Radio	0.126*	0.277***	0.731***	1.662***	0.010	0.184*
	(0.072)	(0.092)	(0.264)	(0.338)	(0.067)	(0.074)
N	1296	1176	1294	1176	1296	1176
Mean	0.599	0.568	2.827	2.665	0.844	0.785
F	3.05	9.07	7.67	24.20	0.02	6.20

(Robust SE) clustered by Sub-Prefecture

* $p < 0.10$, * $p < 0.05$, *** $p < 0.01$

Data source: Afrobarometer Rounds 5 (2013) and 6 (2015)

Notes: *Any Radio* is the share of a Sub-prefecture with access to radio signal above 43 $dB\mu V/m$ and takes values in $[0, 1]$. *Owns radio* takes values 1 if an individual does own a radio device and 0 otherwise. *News radio* takes values 0-4 depending on the frequency with which they listen to news on the radio (0 never, 1 once a month, 2 few times a month, 3 few times a week, 4 every day). *Urban* takes value 1 if the home town is urban and 0 if it is rural.

This evidence is interpreted as suggestive, given the small sample size and that most individuals are surveyed in the main sub-prefecture within each prefecture, a total of 35 sub-prefectures[64]. An increase in the access to an own rural radio station by 10% is associated with a 14, 6% increase in the likelihood that surveyed individuals listen to a rural radio station. There is also some evidence that people with higher access to a particular radio station are more likely to listen to "Ebola Chrono" on that media outlet, but the evidence is weak except for national radio stations. We attach this to the fact that rural stations already had a full program on Ebola when this program started in January 2015 across media outlets.

Finally, we see that people who listen to rural radios are more likely to say that they have heard about Ebola on the Radio, Table 3.7, and this is driven by people who have access to a rural radio from their own community, Table 3.8.

[64]We include only surveyed individuals for which we know the sub-prefecture, leaving us with a sample size of 979 including the capital or of 507 excluding the capital.

Table 3.7: Did you learn about Ebola on the Radio?
Depending on preferred Media outlet reported.

Outcome: Yes, I learned about Ebola on the Radio.

	(1)	(2)	(3)	(4)	(5)	(6)
Listen Any Radio	0.0523	0.0489	0.0485			
	(0.0510)	(0.0521)	(0.0522)			
Listen Rural Radio				0.247**	0.267**	0.251**
				(0.0998)	(0.112)	(0.112)
Listen National Radio				-0.0288	-0.0204	-0.0198
				(0.109)	(0.115)	(0.118)
Listen Private				0.0771	0.0734	0.0637
				(0.0900)	(0.0857)	(0.0870)
Listen Int. Radio				-0.148	-0.155	-0.164
				(0.190)	(0.187)	(0.186)
N	506	506	506	353	353	353
Mean	0.616	0.616	0.616	0.616	0.616	0.616
Cond. listen Radio				Y	Y	Y
Controls	N	Pop	All	N	Pop	All

(Robust SE) clustered by Sub-Prefecture. Sample: 34 Sub-prefectures. Excluding capital.
Controls: N, pop, popdens, wealth index, educ, urban.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Internews Survey (2015)

Beliefs, prevention and treatment uptake

We now show suggestive evidence that broadcast information affected beliefs or knowledge about Ebola, fear of treatment and stated treatment uptake. Using cross-sectional household survey data collected at the end of the outbreak, we explore whether people who own a radio receiver, listen to the radio, report having heard about Ebola on the radio, or have better access to a given radio signal, are more likely to believe in Ebola, have greater knowledge about its symptoms and are more likely to seek treatment or abide by protective measures.

We first run a simple OLS regression to study whether individuals who have heard about Ebola on the media are more likely to know more about Ebola, seek more treatment and wash their hands with chlorine, which helps combat the disease, conditional on receiving information through other means, equation (3.12). Other means of information include

Table 3.8: Did you learn about Ebola on the Radio?
For a given Radio signal.

Outcome: Yes, I learned about Ebola on the Radio.

	(1)	(2)	(3)	(4)	(5)	(6)
Any Radio	0.113	0.0544				
	(0.142)	(0.137)				
Any Rural Radio			-0.00637	-0.0959	-0.00637	-0.0959
			(0.0953)	(0.0891)	(0.0953)	(0.0891)
Own Rural Radio			0.179***	0.174***	0.179***	0.174***
			(0.0287)	(0.0285)	(0.0287)	(0.0285)
National			0.0204	0.0354	0.0204	0.0354
			(0.0356)	(0.0421)	(0.0356)	(0.0421)
Private			-0.0612	-0.0299	-0.0612	-0.0299
			(0.0493)	(0.0586)	(0.0493)	(0.0586)
International			0.108***	0.0866*	0.108***	0.0866*
			(0.0302)	(0.0439)	(0.0302)	(0.0439)
N	353	353	348	348	348	348
Mean	0.616	0.616	0.616	0.616	0.616	0.616
Controls	Pop	All	Pop	All	Pop	All
Cond. Any Radio signal.					Y	Y

(Robust SE) clustered by Sub-Prefecture. Sample: 34 Sub-prefectures. Excluding capital.
Controls: N, pop, popdens, wealth index, educ, urban. Cond. on listening to any Radio.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Internews Survey (2015)

door-to-door campaigns, NGOs or being informed by a doctor. The omitted category is people that have not heard about Ebola or who have heard about it from their family.

$$Behavior_i = \beta_0 + \beta_1 \; EbolaInfo_i + \beta_2 \; EbolaInfo_i^{OnMedia} + \mathbf{X}_{i,d} \, \Gamma + \alpha_r + \epsilon_{i,d} \qquad (3.12)$$

The coefficients of interest are $\beta_1 + \beta_2$, the effect of hearing about Ebola on the media, or β_2, the additional effect of hearing about Ebola on the media, compared to other information sources. In $\mathbf{X}_{i,d}$ we control for individual-level characteristics, including age, education, wealth, gender, as well as whether the location is an urban area, covariates at the sub-prefecture level, such as population, population density, access to electricity and health facilities. We also add distance to the epicenter as control in some specifications, which is a proxy for exposure to the epidemic. We also add region fixed effects α_r, for 8 big regions of Guinea. Standard errors are clustered at the level of a sub-prefecture d.

In addition, given that the OLS estimates are plausibly inflated due to omitted variable bias, since people who seek more information are also more likely to know more about Ebola or have behaviors that help avoid the spread of disease, we instrument having heard about Ebola on the media with the radio signal reception to an own rural radio for the sub-sample of areas with above median access to any rural radio. We study equation (3.13). The omitted category are individuals that have not heard about Ebola or have heard about it through other means, such as family members or from a doctor.

$$Behavior_i = \beta_0 + \beta_1 \; EbolaInfo_i^{OnMedia} + \beta_2 \; EbolaInfo_i^{Door} + \mathbf{X}_{i,d} \, \Gamma + \alpha_r + \epsilon_{i,d} \quad (3.13)$$

The coefficient of interest is β_1, the effect of hearing about Ebola on the media, controlling or not for door-to-door campaigns, $EbolaInfo_i^{Door}$. The exclusion restriction is that the radio signal reception to an own rural radio does not drive the observed behavior other than through its impact on information on Ebola received through the media. In Section 3.5.3 we provide evidence that covariates are balanced around access to an own rural radio, conditional on access to other rural radios. In addition we can control for the distance to the closest transmitter to a rural radio, which is a proxy for the free space signal, and would capture potential endogeneity to the access to a rural radio. Finally, we interpret the results of this exercise as suggestive, given that we lack the time dimension that strengthens our identification in Section 3.5.1.

Results on beliefs, prevention and treatment uptake

The results of our OLS specification show that receiving information about Ebola is predictive of greater Ebola knowledge, belief in its existence and less fear to seek health treatment. However, not every type of information matters for seeking health treatment or using chlorine, Tables C.7-C.9[65].

Those that have heard about Ebola on the media are 50% more likely more likely than those that have received information through other means to say that someone, just like them[66], seeks more health treatment compared to before the epidemic. The question on health treatment is not necessarily related to Ebola. Other measures of neighbors seeking health behavior suggest that overall people that received more information about Ebola are less scared of seeking health treatment but they are more likely to believe that their neighbors have decreased health treatment compared to before, except for people that have received information through the media, who believe that others are more likely to seek health treatment compared to before[67]. The results hold conditional on individual level controls, as well as controlling for distance to the epicenter, which serves a proxy for the potential severity of the epidemic but is not affected by the information treatment of interest.

On the other hand hearing about Ebola on the media is not the best means of information to ensure a greater use of chlorine[68]. Family networks or experiencing close cases of Ebola are positive correlates of the use of chlorine. Chlorine use is a private action that is not observed by others in contrast to seeking treatment or changing burial practices. The common knowledge aspect of having listened to the information on the media, should have little additional benefit on this action[69].

To give further evidence of the hypothesis that the common knowledge aspect of receiving information on the media affects actions that are observed by others but not private actions we test whether the effect varies by greater exposure to media for the former but

[65]We condition on above median access to any rural radio, and control for distance to the closest own rural transmitter for consistency with the reduced form and instrumental variable results. Detailed results on the full sample are available upon request.

[66]In surveys answers are more likely to reflect the true behavior if you ask them about someone just like them.

[67]They are intended as robustness checks of our main measure, presented in Supplementary Appendix Table E.23.

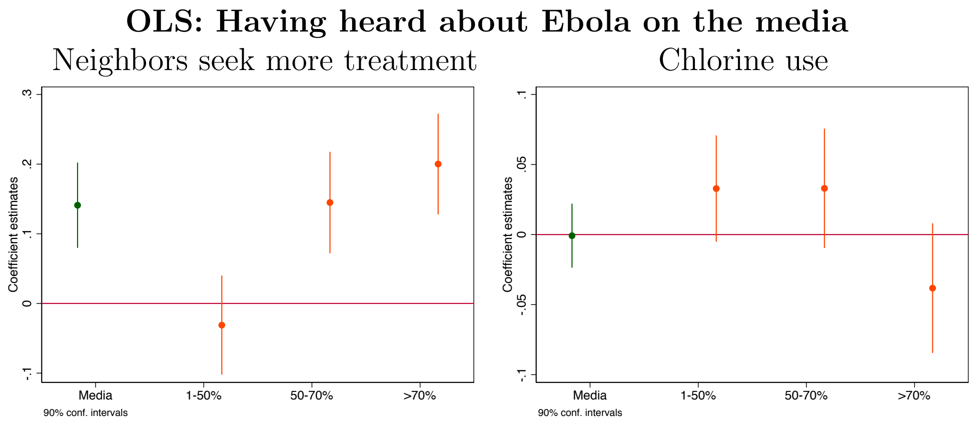
[68]The coefficient is small and negative.

[69]Violating the social norm has no cost in this case, since it is not observed, $\alpha = 0$ in the theoretical model, Section 3.3.

not for the latter. Figures 3.4-3.5 show exactly this pattern, where the treatment is the share of people in the own sub-prefecture, except oneself, that report having heard about Ebola on the media.

These results are suggestive only, due to the obvious selection problem, that people listening to Ebola on the radio are different from people who know about Ebola otherwise. However we find reassuring that although having heard about Ebola on the media is related to ownership of radio devices[70], ownership of radio devices does not predict knowing more about Ebola, nor having greater knowledge about Ebola[71], i.e. some people own radio devices but do not listen to Ebola on the media, because they did not have access to the radio program[72].

Figure 3.4: OLS Access to broadcast information



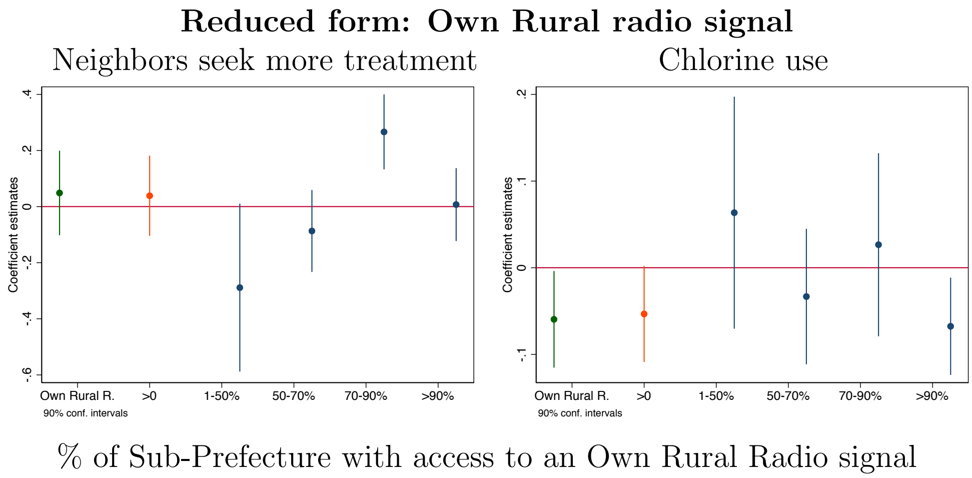
% of people in own Sub-Prefecture that have heard about Ebola on the Media (except yourself)

Notes: Conditional on above median access to an own rural radio signal.
Media: individual has heard about Ebola on the Media
Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS)

We then instrument having heard about Ebola on the radio with the radio signal reception to an own community rural radio. The first stage is strong when we condition on the sub-sample of areas with access to above median access to any rural radio, controlling

[70]Those owning a radio device are $14-17\%$ more likely to have heard about Ebola on the media.
[71]Supplementary Appendix Table E.19
[72]Note that the instrument is having heard about Ebola on the media, not ownership of radio devices.

Figure 3.5: Reduced form effects of access to broadcast information



Notes: Conditional on above median access to an own rural radio signal.
Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS)

for demographic covariates, distance to the epicenter and on the distance to the closest transmitter to a rural radio from the own community, once we control for door-to-door campaigns, with an $F - Stat = 15$ in column (4) in Table C.6[73]. The effect is similar in all cases: an increase by 10 *pp* in access to the signal from a radio station in the own community is associated with a $4 - 9\%$ greater likelihood of having heard about Ebola on the media. The instrument is also significantly related to ownership of radio devices[74].

The reduced form results using radio signal reception to a rural radio from the own community, conditional on above median access to any rural radio, are roughly consistent with the OLS results, Tables C.7-C.9[75]. Greater access to a local radio is positively and significantly associated with greater knowledge and beliefs about Ebola, except when we condition on distance to an own rural radio transmitter. This is consistent with a model in which the benefit of broadcast information compared to other types of information is due to its effect on actions that have social norms attached, rather than its pure information effect. It is also positively associated with neighbors seeking greater health treatment of

[73] The significance test on the instrument has an $F - Stat = 22$ unconditionally, $F - Stat = 84$ conditional on controls, $F - Stat = 82$ including distance to the closest transmitter from any rural radio. When control for the distance to the closest transmitter to a rural radio from the own community we have an $F - Stat = 6$. When in addition we control for door-to-door campaigns we have $F - Stat = 15$, Supplementary Appendix Table E.22.

[74] Supplementary Appendix Table E.20

[75] Detailed results with and without controls are available upon request.

other health behaviors, although the coefficient is not statistically significant. Door-to-door campaigns, however, which lack the common knowledge aspect, are either not or negatively associated with greater health seeking behavior. Fear of seeking treatment is negative and statistically significant when conditioning on the distance to transmitter to a local radio. We also study how the effect varies by percentage of access to an own rural radio, conditional on demographic covariates and distance to the epicenter. The results suggest that sub-prefectures with $70-90\%$ access to an own rural radio are twice as likely to state that their neighbors have not decreased their health seeking behavior, Figure 3.4. On the other hand the effect on chlorine use is zero or negative.

The second stage results are very close in magnitude to the OLS results, and statistically significant, with the same caveats found in the reduced form results, i.e. the effect on beliefs and knowledge about Ebola disappears when conditioning on distance to own radio transmitter, and fear of seeking treatment is negative and statistically significant only when conditioning on this distance. The coefficient on neighbors seeking treatment is larger in this case, but smaller and less precisely estimated than the OLS estimate. The coefficient of chlorine use is negative or zero, Tables C.7-C.9.

We interpret these results as suggestive. They are consistent with a model in which broadcast information affects knowledge and beliefs, but there is an advantage in comparison to other sources of information only when actions have a social cost and they are observable by others. It has no additional benefit on changing private actions, compared to other types of information. Given externalities in health behavior some actions are strategic substitutes and the common knowledge aspect of radio can discourage them, if people expect others to increase their preventive behavior. This can explain the null or negative effects found on chlorine use and the ambiguous effects on seeking health treatment.

This explanation is also consistent with survey evidence from Internews on the program "Ebola Chrono", which was conducted by this organization and then aired across radio stations after January 2015. This program was a synergy and therefore similar across the country. Most people express that what they most liked about the program were the citizen interviews (20%) and the expert interviews (19%), just after the information provided (44%), rather than the presenters themselves (11%), who are not known in the community[76]. Knowing what other citizens believe gives information about changes in what constitutes acceptable behaviors. Individuals also say they learned mostly about preventive measures in these shows (54%), followed by cures (30%). The vast majority is also likely to say that they found the information on preventive measures useful (92%). These preventive behaviors range from washing your hands with chlorine, to laboratory testing and conducting safe burials for family members.

Change in cultural practices

The evolution of cultural practices is studied by looking at the change in burial practices over time as information arrives. Burial practices are a central aspect of culture, they were difficult to change in such a fast pace and a major source of distress during the Ebola epidemic. The outcome studied are refusals by a given community to abide by safe burials[77] conducted by the Red Cross[78].

In Section 3.5.1 we showed in a difference-in-difference design that treatment uptake, measured as the ratio of Ebola deaths in community to Ebola deaths in an Ebola Treatment Unit (ETU), changed over time as a consequence of information transmitted through local radios. We would like to do the same exercise to study burial practices but the data is available only for a short time period after the peak of the epidemic, namely from April to December 2015. We therefore seek a different strategy. In particular we study whether cultural practices change as a consequence of radio emissions or social mobilization campaigns conducted by the Guinean Red Cross over several months. These radio emissions

[76] Supplementary Appendix Table E.24

[77] Once the safe burials, i.e. conducted with personal protective equipment (PPE), were accommodated to the local customs, which included a religious ceremony, they became known as safe and dignified burials (SDB).

[78] National Red Cross and Red Crescent Society

were emitted by Rural radios, as well as by mobile radio transmitters. We have weekly data at prefecture level from April to December 2015 on the number of safe and dignified burials conducted by the Red Cross and the number of burials refused by a given community, as well as the number of radio emissions aired, the number of volunteers conducting social mobilization campaigns, whether these were preventive or in response to resistance behavior, as well as the number of people transported, cholera kits, surveillance efforts and other activities conducted by the Red Cross.

We study in a panel estimation framework with location and time fixed effects whether burial practices changed over time following radio emissions from the Red Cross. Radio shows and social mobilization campaigns are endogenous to the spread of Ebola and to the change in behavior over time. In particular, communities that were more likely to refuse safe burials or treatment, show other form of resistance behavior or were more affected by the epidemic, are exactly the places that were targeted by the Red Cross to receive more information and assistance. We will take this selection effect into account by studying the effect of radio emissions this month on burial refusals in the following month, conditional on radio emissions one month before, as well as conditioning on social mobilization campaigns that were realized in response to resistance behavior, and other covariates. The strategy is summarized in equation (3.14).

$$
\begin{aligned}
Refusal_{d,t+m} = & \sum_{j=0,1,2} \beta_j^m \; RadioProgram_{d,t-j}^{RedCross} + \sum_{j=0,1,2} \gamma_j^m \; SocialMob.Prev._{d,t-j}^{RedCross} \\
& + \sum_{j=0,1,2} \delta_j^m \; RadioProgram_{d,t-j}^{RedCross} \times SocialMob.Prev._{d,t-j}^{RedCross} + \mathbf{X}_{d,t}\,\Gamma + \alpha_d + \lambda_t + \epsilon_{d,t} \\
& \text{for all } m \in [0,4]
\end{aligned}
\tag{3.14}
$$

The effect of interest is β_0^m, for different time horizons $m \in [0,4]$, which is the effect of radio emissions this month on burials m months later, conditioning on observables that should capture the selection effect, i.e. the fact that the Red Cross emits radio shows in areas where they expect to find resistance. While radio shows were not randomly assigned, the selection effect means that $\hat{\beta_0^m}$ is likely a lower bound of the effect of these radio emissions on burial practices m periods ahead. In addition we also see whether social mobilization campaigns that were realized for prevention of resistance behavior affected refused burials, γ_0^m and whether there are complementarities, δ_0^m.

The outcome variable $Refusal_{d,t+m}$ are the refusals of safe burials conducted by the Red Cross in 100'000 per capita m months ahead. In this case d denotes prefecture (34). Standard errors are clustered at prefecture $\times$ semester to allow for some level of serial dependence across time.

The controls in $\mathbf{X}_{d,t}$ include the total number of burials or Ebola deaths in period t, trends by population, population density and distance to the epicenter, which should capture the likelihood that Ebola spreads, as well as the number of other activities the Red Cross conducts in period t, such as transport of patients, disease surveillance or the provision of cholera kits. We also exploit the fact that the Red Cross classifies some of the social mobilization campaigns as responsive to resistance behavior, which we use as control to capture the selection effect, i.e. we add $\sum_{j=0,1,2} SocialMob.Response_{d,t-j}^{RedCross}$ in the set of controls.

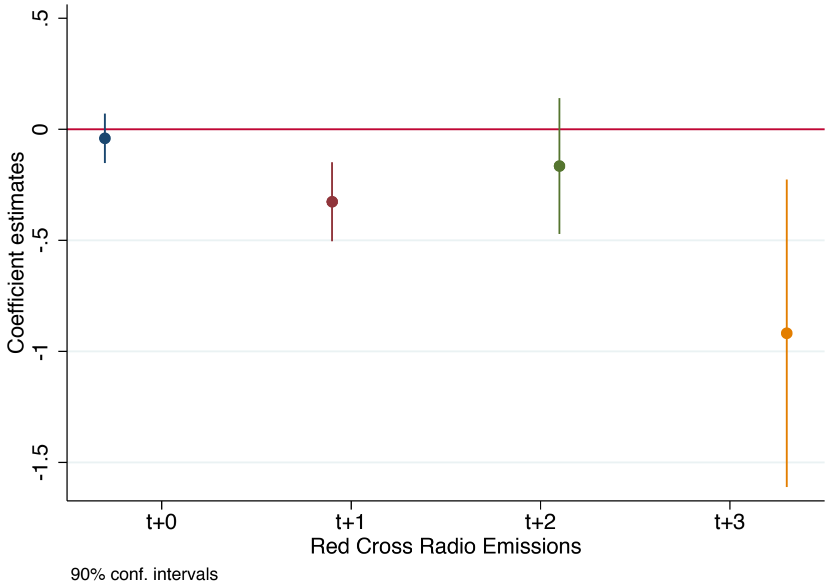
Results to the evolution of cultural practices

The results indicate that a one-standard deviation increase in the number of radio emissions this month is followed by a drop in refused burials in 100'000 per capita by $0.16-0.33$ the next month and 0.92 after three months, Figure 3.6 and Table C.10. This is equivalent to a $40-85\%$ of a standard deviation change in the number of refused burials this month or 3 standard deviations after three months. In terms of number of radio emissions per prefecture, one additional radio show emitted by the Red Cross in a given month is followed by a drop in refused burials in the following month, by 0.05 or 48% of the average number of refusals in a given month[79]. This means that 20 additional radio shows are required to ensure one less burial refusal in the next month. In the long term these

[79]Supplementary Appendix Table E.26.

radio emissions would be followed by 4 less refused burials three months ahead[80]. The effect of social mobilization campaigns or their interaction with radio emissions is small, ambiguous and not robust to different specifications[81]. We take these results as suggestive. They are consistent with a model in which radio emissions have a greater impact on cultural practices than social mobilization campaigns due to their common knowledge aspect. People know that everybody knows that the social norm is shifting and that they would incur little social cost by abiding to safe burials.

Figure 3.6: Refused burials in 100k per capita



Data source: International Federation of the Red Cross in Guinea, April-December, 2015

The outcome variables are *total refused burials*, an average of 0.33 per month, and *refused burials* in 100'000 per capita, with monthly mean (std. dev.) 0.11 (0.39). *Red Cross Radio* are the number of radio emissions aired and here we standardized the original variable which had mean (std. dev.) 0.85 (3.29). Plotted coefficients are separate regressions, conditional on social mobilization campaigns, as well as conditional on demographic controls, social mobilization and other efforts by the Red Cross. We also control for the potential interaction effects between social mobilization and radio emissions. See Table C.10 and Supplementary Appendix Table E.25.

[80]The effect is not statistically significant for month 3 when using the non-standardized variables but it is otherwise, Table C.10

[81]Radio emissions and social mobilization campaigns designed for prevention appear to be complements in the short run, i.e. at $t + 1$, but substitutes in the long run, i.e. at $t + 3$.

Local information

This Section further examines the channels through which local information matters for the spread of a disease. First we study the possibility of a political accountability channel explored in other settings (Besley and Burgess, 2002; Eisensee and Strömberg, 2007), namely that higher access to local information leads institutions to provide more public goods because citizens are more able to hold them accountable. Secondly, we discuss the differences in language, ethnic groups and trust as potential mechanisms underlying the persuasiveness of information provided via local rather than another rural radio.

I. Political accountability

In theory, broadcast information could have affected social unrest and the spread of Ebola through its impact on the provision of public goods, due to a government accountability channel (Besley and Burgess, 2002; Eisensee and Strömberg, 2007). That is, areas with higher access to local information would make the government more accountable for its policies and hence the latter would make a greater effort to provide public goods, such as treatment, to these areas. This is unlikely to be the main channel in this setting, for a number of reasons. Firstly, while private motives, corruption or other motives are possible, it is plausible to think that in the case of a deadly and contagious disease that spreads rapidly throughout the country, the government authorities will eventually have as their objective to stop its rapid spread. Secondly, the whole apparatus set in place to halt the spread of Ebola included NGOs, such as Doctors without Borders (MSF), the Red Cross and was then coordinated under the auspices of the WHO. In fact, the intervention was criticized for taking little account of social unrest and local populations, as illustrated by the imposition of quarantines and cremations in Liberia (Moon, 2015) and the civil violence that arised, Chapter 2. To explore this possibility, however, we study whether the presence of Ebola treatment units (ETUs), laboratories and Community care centers (CCCs) is predictive of radio signal exposure, controlling for the distance to the epicenter, population and population density, which are predictors of the spread of the disease. We find that while general access to any radio is positively related with availability of public goods, this is not the case for local radios, conditional on access to other radios or other rural radios, Table 3.9. We look both at the shortest distance to an ETU, laboratory or CCC ever available, as well as their total number or the number of them in a given sub-prefecture in 100'000 per capita[82]. There is evidence that access to any rural radio is related to greater availability of CCCs, but these are hospitals that pre-date the Ebola epidemic. This is consistent with a political accountability channel occurring prior to the epidemic outbreak (Besley and Burgess, 2002; Eisensee and Strömberg, 2007). There is no difference in any of the public goods across areas with different exposure to a local radio, however. Moreover, we are conditioning on the availability of these public goods in all our specifications. Finally, in Section 3.5.3 we show that the establishment of ETUs and laboratories does not change significantly over time in areas with varying exposure to a local radio.

II. Language, ethnic groups and trust

The Ebola information campaigns were similar across rural radio stations and conditional on a given rural radio, they were exactly the same for people listening to it from within the prefecture in which the radio is located compared to people listening to it from another prefecture. Why would it matter then whether the information is received from a rural radio station from the own community?

The source of information may be important in determining how persuasive the information can be. The rural radios produced an information campaign on Ebola that was sustained, contrary to the private radio stations, and the contents were persuasive, rather than factual or normative, compared to the national radio stations, as they invited Ebola survivors to their talks, as well as local, traditional or religious leaders. In addition those

[82]Supplementary Appendix Tables E.27-E.28

Table 3.9: Public Good provision by access to Radio

Shortest distance to a public good

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Distance to ETU	-0.008*	0.009	0.004	-0.000	-0.004	-0.003	-0.000
	(0.004)	(0.006)	(0.006)	(0.007)	(0.003)	(0.007)	(0.007)
Distance to Lab	-0.014***	0.002	-0.009*	-0.004	0.004	0.004	0.001
	(0.003)	(0.005)	(0.005)	(0.007)	(0.005)	(0.006)	(0.007)
Distance to CCC	-0.000	0.002*	0.002	0.003	-0.003***	-0.002	-0.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Any Radio		0.484***	0.401***	0.368***	0.898***	0.586***	0.012
		(0.043)	(0.052)	(0.051)	(0.029)	(0.052)	(0.097)
Any Rural Radio							0.639***
							(0.109)
N	331	331	331	331	331	331	331
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (ETU,Lab,CCC)	0.00	0.13	0.12	0.39	0.00	0.65	0.99
p-val (sum ETU,Lab,CCC)	0.00	0.07	0.70	0.89	0.57	0.91	0.94

(Robust SE). With region fixed effects (8 regions).
Excl. capital. Controls: population, population density, geographic area, distance to epicenter and their square.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: *Distance to ETU*, *Distance to Lab* and *Distance to CCC*, are the smallest log-distances to an Ebola Treatment Unit (ETU), laboratory (Lab) and community care center (CCC) ever available, with mean (std. dev.) 10.5 (4.02), 10.5 (4.4) and 6.5 (7.9), respectively. ETUs and laboratories are created ad-hoc during the Ebola outbreak. CCCs are hospitals that exist prior to the epidemic outbreak. We control for variables correlated with the spread of the disease.

with access to their own community radio station were more likely to know the speaker, know someone who knows the speaker, or have someone from their own community as presenter, compared to those with access to a rural radio station from another community. Trust is likely to be important in transmitting information that is sensitive and opposed to prior beliefs.

In Section 3.5.2 we showed that radio signal reception to any radio station is correlated with ownership of a radio device and listening to news on the radio. However, when we look at who learned about Ebola on the radio, only those that report listening to a rural radio station are more likely to say that they have learned about Ebola on the radio and when we look at reduced form results using our radio signal measure, we see that this is driven by sub-prefectures with higher access to an own rural radio station. Section 3.5.2

moreover suggests that the extra that they learned on the radio was related to treatment uptake or other people's actions, rather than about the disease per se, in comparison to people who learned from other information sources.

We next study the possibility that ethnic groups or language and trust plays a role in explaining the difference between own community and any rural radio station. This channel was proposed by the director of rural radios in Guinea, and a reason for creating new rural radios later in the epidemic, so that every prefecture would have their own rural radio[83]. Guinea is a very diverse country, with about 24 ethnic groups with different customs and languages. In our sample the average sub-prefecture has an ethnic fractionalization index of 24%, which means that the probability that two individuals belong to different groups is about 1/4 on average[84]. Rural radio stations take this into account and emit radio programs in a number of languages. They report using an average of 3 languages and a maximum of 6, apart from French, according to surveys conducted by the author[85]. Guineans are often fluent in several languages. However, language is still a potential barrier to communication and moreover languages and ethnic groups coincide, and people might trust more people of their own ethnic group. Survey data reveals that the average Guinean rarely thinks that their ethnic group is treated unfairly and they more likely to state a stronger national identity rather than ethnic belonging[86]. However, on average only 28% of individuals state that most people can be trusted, and the other 72% state that one has to be very careful in trusting most people. There is also low trust in institutions, such as the president or the local council.

We conduct a series of balance tests across radio signal reception to see whether language, ethnic groups and trust levels predict access to a local radio[87]. This exercise tells us

[83]These were launched after our effects take place, namely after February 2015.

[84]*Fractionalization* measures the probability that two individuals belong to different groups. It's a Herfindahl index that goes from 0 (all belong to the same group), to 1 (total diversity). It is defined as $F = \sum_{i=1}^{m} n_i(1 - n_i)$, where m is the number of groups and n_i is the relative size of each group.

[85]The Rural radio of Boke reported using Susu, Fulla, Landuma, Diakanke, Nalou, Mikhifore and French.

[86]Supplementary Appendix Table E.29

[87]Supplementary Appendix Tables E.30-E.35

whether ethnic composition or languages spoken varies across areas with or without access to a local radio station. The results show that there is a different composition in terms of language or ethnic groups, but the differences are not statistically significant when controlling for trust in institutions and urban infrastructure. On the other hand, areas with higher access to a rural radio from their own community have higher levels of trust in their local council across different specifications. To test the hypothesis that higher trust in the local council is an outcome of having access to a radio from the own community, rather than something that differentiates areas with or without a local radio per se, we run the exact same balance test but using trust in the local council measured after the peak of the epidemic instead of pre-epidemic levels of trust. This post-epidemic measure of trust in local councils is not predictive of access to local radios, conditional on the same set of covariates[88]. After the peak of the epidemic new rural radios were created so that everybody would have an own rural radio station. This is consistent with the demand-side effects required for a political accountability channel to occur, namely that citizens trust more their local politicians when they have higher access to local information. Finally, to rule out that the results of this paper are entirely driven by trust in local councils and that having a local radio is a proxy for it, we control for trust in our main empirical strategy, Section 3.5.1. While the effects are somewhat smaller, they are not entirely driven by it[89].

The results give suggestive evidence of the role of trust in local institutions in explaining why local information matters more than information from other communities, conditional on receiving the same information.

3.5.3 Robustness and validity checks

In this Section we provide robustness and validity checks of our main empirical strategy. We first study deeper the identifying assumptions and then provide alternative specifications.

[88]The coefficient is negative and not statistically significant, Supplementary Appendix Table E.35
[89]See for instance Table C.2.

I. Parallel trends assumption

The key identifying assumption in a difference-in-difference strategy is that the trends in the spread of Ebola would be the same in places with varying levels of radio exposure in the absence of treatment. There are three main validity checks we conduct. First we have shown in Section 3.5.1 that the spread of Ebola is similar in areas with varying levels of access to an own rural radio, conditional on other radios, prior to the start of the rural radio campaign. Secondly we study whether the Ebola response changes over time differentially for areas with distinct access to their own community radio station, conditional on controls. Thirdly we assess that areas with access to an own community radio station are not fundamentally different from other areas. While this is not necessary in a difference-in-difference design, it strengthens the empirical set-up, given the potentially unexpected dynamics of the spread of a disease. Finally we study the spread of other diseases, using data available at the level of a prefecture.

Time-varying confounders : The second validity check requires studying other potential confounders changing over time differentially for areas with distinct levels of exposure to local radios. The main suspect are national and international efforts to contain the epidemic. The best measure we have is the establishment of health facilities, such as Ebola treatment units (ETUs) and laboratories. Given that international aid arrives much later than the start of the rural radio campaign, namely after August 2014, when the WHO declares the Ebola epidemic an 'international public health emergency', there is not much variation in health facilities before that. Instead we study whether there is something that changes differentially in areas with distinct exposure to local radios around the seventh month after the start of the rural radio campaign, given that we observe the effect at that time. We find that this is not the case, when looking at the time-varying distance to the closest ETU or the number of ETUs or the number of ETUs adjusted by population, with or without controls, Figure C.5. The patterns are less impressive when we look at the establishment of laboratories, but we still see no statistically significant change in the distance to the closest laboratory or the number of laboratories per capita, conditional on controls, Figure C.6.

Baseline characteristics correlated with the spread of disease : We also assess whether baseline covariates, correlated with the spread of disease, are balanced around access to an own community radio station, conditional on access to other radios. If areas with distinct access to an own community are fundamentally different from each other, one would think that in absence of information treatment the disease might not have continued the parallel trends observed prior to the start of the information campaign.

Since our treatment variable is continuous we run a regression with each radio signal measure as dependent variable on a number of covariates (Pei et al., 2018). We exclude the capital to understand what differentiates the rest of the country.

We first assess whether areas with higher access to radio are more densely populated or closer to the epicenter or first Ebola case. We find that areas with higher access to some radio station are more densely populated, but not different in terms of distance to the epicenter[90]. On the other hand, sub-prefectures with access to an own rural radio station are somewhat larger and therefore less densely populated compared to areas with access to rural radio stations from other communities. Since population density is an important correlate of disease spread we will control for population and population density in all our specifications.

Secondly, other important covariates, such as wealth, education, religious beliefs, infrastructure, are more predictive of having access to any radio, or conditioning on any radio, they are predictive of having a national or a private radio, but not a rural radio[91]. These covariates are not predictive of having access to an own community radio, once we control for having access to any rural radio.

[90] Supplementary Appendix Table E.12.
[91] Supplementary Appendix Table E.13.

Other diseases : Finally, we study the spread of other diseases during the year prior to the Ebola outbreak, aggregated by prefecture. Having access to any radio station, compared to not having access to it, is correlated with the likelihood of the spread of some diseases[92]. When looking at distinct media outlets, conditional on having access to any radio, there are important differences in the spread of disease for areas with varying access to the national or private radio[93]. However, areas that have access a rural radio in their own prefecture are similar to other areas with some access to radios[94].

II. Alternative specifications

Lagged dependent variable specification : The theoretical model summarized in equation (3.5) suggests a specification with a lagged dependent variable. Since we are running a short panel with 16 periods in the event study with $j \in [-5, 10]$, the inclusion of both fixed effects and a lagged dependent variable is problematic (Nickell, 1981). We can run however an alternative regression to equation (3.7), replacing α_d with the lagged dependent variable $log(Ebola + 0.01)_{d,t-1}$, namely:

$$\begin{aligned} log(Ebola + 0.01)d, t = \rho \; log(Ebola + 0.01)d, t-1 + \beta_j \; Radio_d^{Local} \times \mathbb{1}_t(j)^{Campaign} \\ + \sum_{k \neq Local} \gamma_j^k \; Radio_d^k \times \mathbb{1}_t(j)^{Campaign} + \mathbf{X}_{d,t} \, \Gamma + \lambda_t + \epsilon_{d,t} \qquad (3.15) \end{aligned}$$

The coefficients $\{\beta_j\}_{j \geq 0}$ are a lower bound estimate of the true effect of local radios on the spread of Ebola (Angrist and Pischke, 2008).

The results from this specification are similar to the fixed effects specification[95]. The coefficient is identical in the seventh month but somewhat lower coefficients thereafter, although only the coefficient in the tenth month is significantly smaller.

[92]Supplementary Appendix Table E.14
[93]columns (2)-(5)
[94]column (6)-(7)
[95]Supplementary Appendix Table E.7 and Figure E.3.

Different measures of Ebola : Our preferred specification uses $log(Ebola + 0.01)$ as outcome variable. The reason is that this is the closest model to the epidemiological theory, Section 3.3. However, we also do the same empirical analysis with $log(Ebola + 1)$ as outcome variable, as well as the number of Ebola cases, or alternatively we adjust by population, taking $log(ebola + 1)$ and *ebola* as outcome variables, where *ebola* is the number of Ebola cases in 100'000 per capita[96]. We find identical results in terms of the timing of the drop in Ebola cases and also effects of similar magnitude. When the outcome variable is $log(Ebola + 1)$ we find an effect of $8.5 - 13\%$ drop in the number of Ebola cases due to a 10 *pp* increase local radios, seven months after the campaign[97]. When the outcome is the number of Ebola cases the effect is a 20% drop. Finally, when *ebola* is measured in 100'000 per capita, the effect in the linear model is a 35% drop in this outcome. In the log-linear model with $log(ebola + 1)$ as outcome, the implied effect is a 10% drop.

3.6 Conclusion

The Ebola epidemic in Western Africa in 2014-15 was a human tragedy, as well as a major shock that generated a great influx of state capacity in the form development assistance and required the adoption of new medical technologies and a change in cultural practices to halt the outbreak, which led to social unrest and the spread of rumors, countering containment efforts.

This paper shows that sustained access to a local radio program informing about protective measures, encouraging treatment, addressing Ebola rumors and new burial practices, lowered social resistance behavior, increased treatment uptake and led to a drop in infected cases seven months after the start of the campaign, compared to having access to other

[96] Results are presented in Tables E.3-E.6

[97] In the log-linear model with $log(Ebola + 1)$ the coefficients require a greater adjustment than the standard case, given by the following formula: $(e^{\hat{\beta}\times 0.10} - 1) \times \frac{y_0+1}{y_0} \times 100\%$, where y_0 is the average *Ebola* in the absence of local radios.

campaigns or the same campaign from other radios. A back-of-the-envelope calculation suggests that around 303 Ebola infections could have been spared if all areas with access to a rural radio station had their own local radio from the beginning of the outbreak, that is 8% of the total number of Ebola cases. This is consistent with evidence showing that local newspapers are more likely to increase salience of public goods, compared to national or international news (Besley and Burgess, 2002), and the role of community radio stations in providing information to voters, in neighboring Sierra Leone (Casey, 2015). We find suggestive evidence that broadcast information affected cultural norms, such as burial practices, and facilitated technological adoption, but there is no evidence of impacts on private actions. This differs from other sources of information, such as social mobilization strategies, which do not seem to impact burial practices. On the other hand, knowing an Ebola victim or receiving information from family members is more predictive of private actions, such as chlorine use. The findings suggest that the common knowledge of radios serves as a coordination device and is key in changing health habits that are attached to cultural practices. This is consistent with evidence in other contexts showing that radios can affect social norms (Paluck, 2009; Paluck and Green, 2009).

Our results support the hypothesis often repeated by local actors and anthropologists that local knowledge is key in affecting significant development outcomes. This work suggests that cultural practices can change, rumors can subside, in matter of months, if information is convincing and trustworthy. This paper is a step forward in our understanding of local media as a means to improve development outcomes through its impact on cultural practices.

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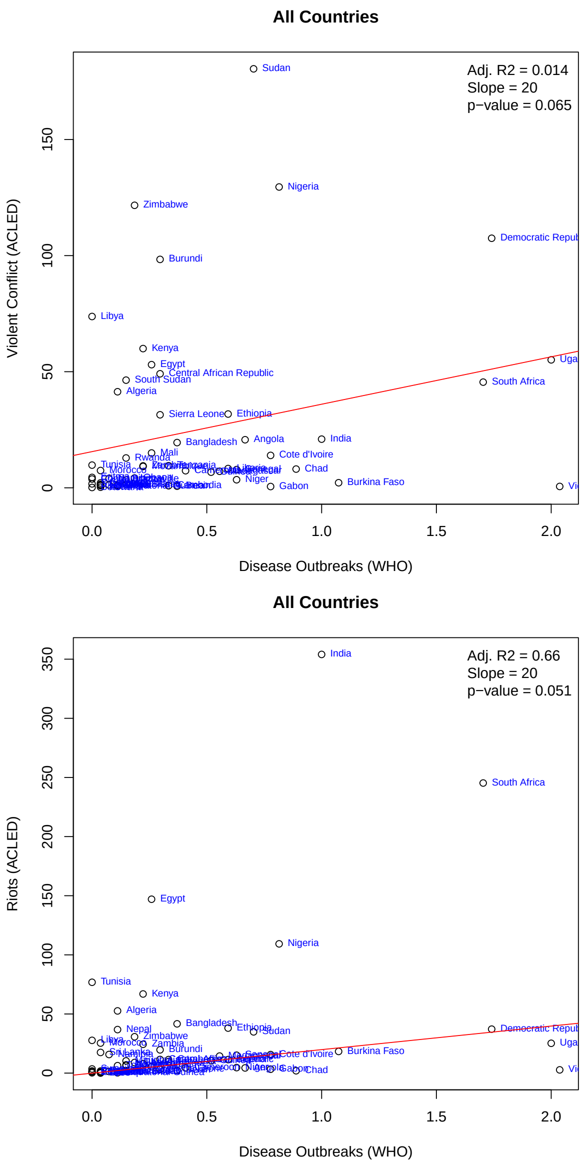
Appendices

A Appendix to Chapter 1

Figure A.1: Disease outbreaks and Violent Conflict or Riots



Notes: Conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). Disease outbreak alerts (excluding updates) (WHO). Observations: 67 countries over 1997-2016 in Africa, South and South East Asia, Central America, the Caribean and Mexico (excluding the outliers Pakistan and Somalia).

Table A.1: Event study of Disease outbreaks on Conflict
Heterogeneous effects by Institutions / Health Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
disease(t)	-8.485	53.09	52.28	41.06	178.6**	139.6***	48.33	59.96
	(28.92)	(34.73)	(34.48)	(36.79)	(83.49)	(45.62)	(61.23)	(35.90)
disease(t) × Polity IV^{High}				37.86				
				(111.00)				
disease(t) × Political Rights^{High}					-343.1**			
					(151.93)			
disease(t) × Civil Liberties^{High}						-149.0**		
						(58.03)		
disease(t) × Freedom of Expression^{High}							-17.98	
							(83.31)	
disease(t) × Health Expenditure (t-1)								-8.965
								(26.93)
Observations	648	577	577	577	577	577	577	577
R-squared	0.814	0.880	0.881	0.881	0.896	0.882	0.882	0.881
Mean	555.5							
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Year × Continent FE	Y	Y	Y	Y	Y	Y	Y	Y
Population(t-1),GDP(t-1)		Y	Y	Y	Y	Y	Y	Y
disease(t-1)			Y	Y	Y	Y	Y	Y
(1, disease(t-1)) × Institutions(t-1)				Y	Y	Y	Y	
(1, disease(t-1)) × Health Expenditure(t-1)								Y

(Robust SE) clustered by country
Where Institutions are demeaned variables.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD) at $(t-1)$, and disease outbreaks one year before and also at $(t-1)$. Weighted by average population over the sample period. For full specification equation (1.3). Definitions: *Conflicts*: disease-motivated conflicts according to the description of the event (ACLED). Disease outbreak alerts (excluding updates) (WHO). *Civil Liberties*: civil liberties, aggregating freedom of expression and belief, associational rights, rule of law, individual rights; *Political Rights*: electoral process, political pluralism and participation, functioning government, with higher values indicating more liberties or rights (Freedom House Index); *Polity IV* (2): captures this regime authority spectrum on a 21-point scale ranging from -10 (autocracy) to +10 (consolidated democracy) (Center for Systemic Peace). Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico (excluding Somalia, Pakistan (outliers) and South Sudan (incomplete data on civil liberties)).

Table A.2: Event study of Disease outbreaks on Health or Disease-related Conflict Heterogeneous effects by Institutions / Health Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
disease(t)	0.227	2.488**	2.438**	1.938	8.370**	5.782***	2.352	2.801**
	(1.01)	(1.14)	(1.15)	(1.33)	(3.51)	(1.77)	(2.36)	(1.17)
disease(t) × Polity IV^{High}				1.700				
				(4.59)				
disease(t) × Political Rights^{High}					-16.65**			
					(6.97)			
disease(t) × Civil Liberties^{High}						-5.747**		
						(2.72)		
disease(t) × Freedom of Expression^{High}							-0.656	
							(3.27)	
disease(t) × Health Expenditure (t-1)								-0.320
								(1.11)
Observations	648	577	577	577	577	577	577	577
R-squared	0.811	0.875	0.876	0.876	0.892	0.876	0.876	0.876
Mean	20.76							
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Year × Continent FE	Y	Y	Y	Y	Y	Y	Y	Y
Population(t-1),GDP(t-1)		Y	Y	Y	Y	Y	Y	Y
disease(t-1)			Y	Y	Y	Y	Y	Y
(1, disease(t-1)) × Institutions(t-1)				Y	Y	Y	Y	
(1, disease(t-1)) × Health Expenditure(t-1)								Y

(Robust SE) clustered by country

Where Institutions are demeaned variables.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD) at $(t-1)$, and disease outbreaks one year before and also at $(t-1)$. Weighted by average population over the sample period. For full specification equation (1.3). Definitions: *Conflicts*: disease-motivated conflicts according to the description of the event (ACLED). Disease outbreak alerts (excluding updates) (WHO). *Civil Liberties*: civil liberties, aggregating freedom of expression and belief, associational rights, rule of law, individual rights; *Political Rights*: electoral process, political pluralism and participation, functioning government, with higher values indicating more liberties or rights (Freedom House Index); *Polity IV* (2): captures this regime authority spectrum on a 21-point scale ranging from -10 (autocracy) to +10 (consolidated democracy) (Center for Systemic Peace). Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico (excluding Somalia, Pakistan (outliers) and South Sudan (incomplete data on civil liberties)).

Table A.3: Event study on Riots by Polity IV (2) (above mean)

	Conflicts								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	8.141	-33.40**	0.0211	-14.37	-64.59	57.06*	175.0	208.0**	77.96
	(9.98)	(14.67)	(23.73)	(10.28)	(64.33)	(31.12)	(110.63)	(100.84)	(78.76)
disease(t) × Polity IV^{High}	2.443	47.04***	37.25	48.29	209.2	28.28	-158.2*	26.12	-56.47
	(12.94)	(12.00)	(38.49)	(40.22)	(127.48)	(90.63)	(86.20)	(240.19)	(75.06)
Polity IV^{High}	-49.32	-102.6	-114.9	-72.68	-242.9	31.92	754.5	113.9	106.0
	(31.50)	(76.35)	(93.62)	(63.86)	(159.62)	(188.74)	(547.47)	(120.27)	(172.72)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.584	0.522	0.583	0.554	0.898	0.886	0.879	0.876	0.896
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), disease(t+j-1), disease(t+j-1) × Covariate (t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Event study on Riots by Polity IV (2) (demeaned)

	Conflicts								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	6.445	-18.13	10.53	0.0182	8.899	80.76*	143.6	234.5*	54.37
	(7.76)	(15.40)	(13.24)	(11.63)	(42.53)	(44.09)	(91.45)	(136.38)	(63.66)
disease(t) × Polity IV(t-1)	-1.370	1.479	-0.404	2.833	22.21	10.39	23.89*	29.08	44.64*
	(2.81)	(2.65)	(4.53)	(4.54)	(14.61)	(7.80)	(13.72)	(25.11)	(24.97)
Polity IV(t-1)	-1.902	-6.469	-1.742	-3.263	6.259	50.24	13.23	-22.26	-46.00**
	(3.69)	(9.10)	(7.16)	(4.01)	(30.63)	(37.60)	(16.39)	(15.28)	(21.03)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.566	0.487	0.548	0.545	0.898	0.888	0.876	0.879	0.897
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), disease(t+j-1), disease(t+j-1) × Covariate (t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Event study on Riots by Political Rights (above mean)

	Conflicts								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	10.66	-4.420	9.019	-8.873	52.90	177.9**	133.0	222.3**	82.29
	(12.06)	(7.16)	(22.95)	(11.66)	(34.23)	(74.78)	(91.62)	(104.27)	(77.34)
disease(t) × Political Rights^{High}	-9.280	-35.35	7.564	29.11	-135.2	-308.6**	-30.91	-18.00	-127.7**
	(19.74)	(48.12)	(35.16)	(22.37)	(84.93)	(133.63)	(71.92)	(206.64)	(59.46)
Political Rights^{High}	-20.53	29.06	3.963	-27.22	199.0*	844.7*	-130.1	120.5	236.3
	(21.12)	(55.70)	(31.23)	(57.18)	(114.95)	(441.17)	(237.77)	(122.15)	(252.40)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.571	0.494	0.549	0.548	0.898	0.901	0.874	0.876	0.895
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), disease(t+j-1), disease(t+j-1) × Covariate (t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Event study on Riots by Political Rights (demeaned)

	Conflicts								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	4.312	-19.84	5.063	-1.246	18.27	83.00**	162.1*	257.7*	67.68
	(7.44)	(16.13)	(12.56)	(15.40)	(47.69)	(33.28)	(84.64)	(132.34)	(56.16)
disease(t) × Political Rights(t-1)	-1.103	-0.183	-2.283	-0.810	5.769	6.245*	12.23**	15.40	23.67**
	(1.08)	(1.64)	(1.69)	(1.41)	(5.81)	(3.15)	(5.42)	(11.44)	(10.10)
Political Rights(t-1)	0.803	3.100	4.177	5.062	31.20	11.59	9.353	-0.640	0.578
	(1.31)	(2.66)	(3.46)	(7.95)	(39.00)	(35.22)	(22.88)	(17.83)	(23.32)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.565	0.485	0.555	0.546	0.898	0.888	0.877	0.881	0.898
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), disease(t+j-1), disease(t+j-1) × Covariate (t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

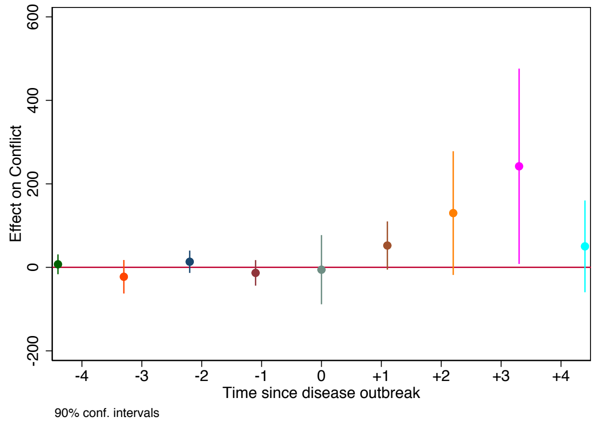
Table A.7: Event study on Riots by Civil Liberties (above mean)

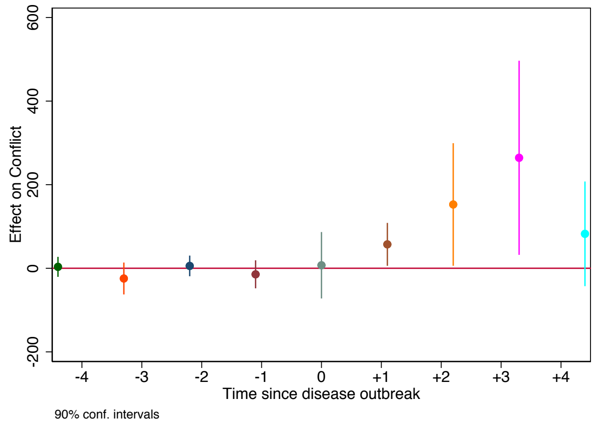
	Conflicts								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	10.29	-17.10	35.00	26.50	-55.15	139.9***	355.7***	356.8**	274.0*
	(11.71)	(32.06)	(26.97)	(29.78)	(75.39)	(35.59)	(118.41)	(157.26)	(154.59)
disease(t) × Civil Liberties^{High}	-5.244	-0.497	-38.55	-50.13	140.1	-127.1***	-399.2***	-207.3	-365.7**
	(9.57)	(28.14)	(26.44)	(32.28)	(112.68)	(44.17)	(113.58)	(251.86)	(153.09)
Civil Liberties^{High}	-2.865	-0.198	-2.152	42.43	-601.3**	187.3*	825.9**	-361.1	1089.4**
	(13.20)	(12.52)	(16.27)	(43.83)	(239.29)	(99.96)	(410.92)	(255.19)	(477.94)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.562	0.485	0.557	0.554	0.905	0.887	0.888	0.880	0.909
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), disease(t+j-1), disease(t+j-1) × Covariate (t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

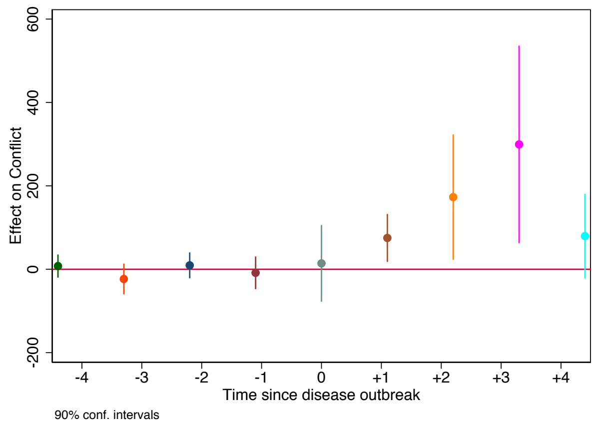
Figure A.2: Event study of Disease outbreaks on Conflict incidence

Outcome: Conflict events in year t





Conditional on civil liberties (demeaned) × (1, disease outbreaks)

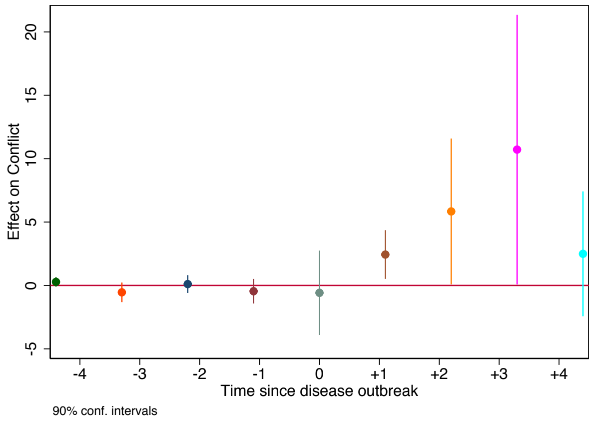


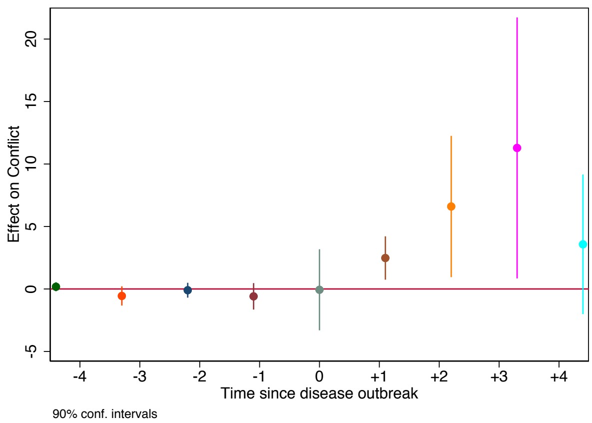
Conditional on political rights (demeaned) × (1, disease outbreaks)

Notes: Conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD) at $(t-1)$, and disease outbreaks one year before and also at $(t-1)$. Weighted by average population over the sample period. For full specification equation (1.2). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). Disease-motivated conflicts according to the description of the event. Disease outbreak alerts (excluding updates) (WHO). Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico.

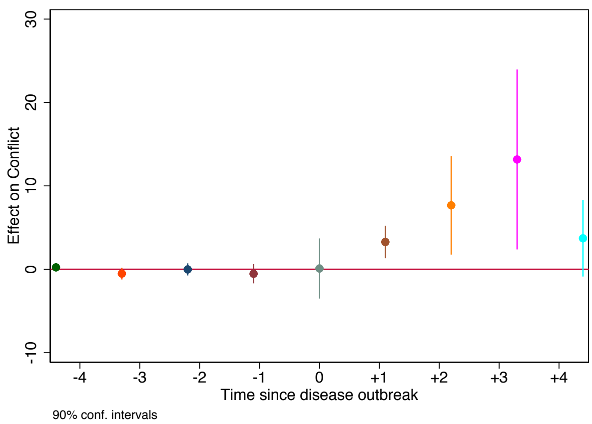
Figure A.3: Event study of Disease outbreaks on Health or Disease-related Conflict

Outcome: Conflict events in year t





Conditional on civil liberties (demeaned) × (1, disease outbreaks)

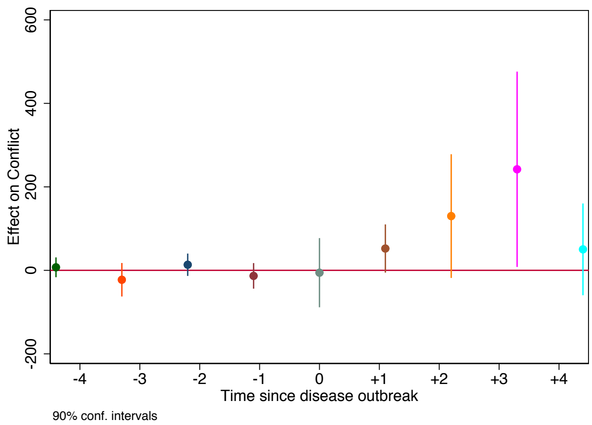


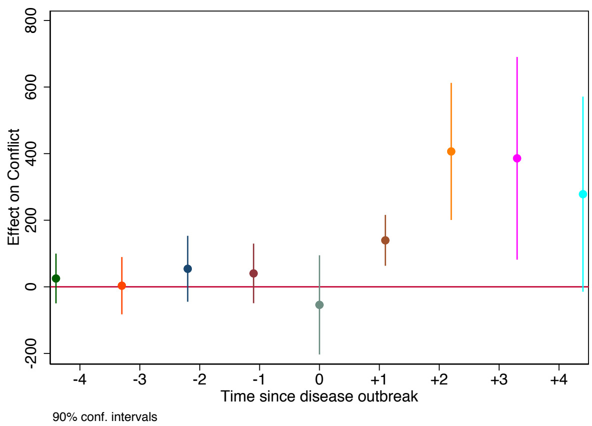
Conditional on political rights (demeaned) × (1, disease outbreaks)

Notes: Conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD) at $(t-1)$, and disease outbreaks one year before and also at $(t-1)$. Weighted by average population over the sample period. For full specification equation (1.2). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). Disease-motivated conflicts according to the description of the event. Disease outbreak alerts (excluding updates) (WHO). Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico.

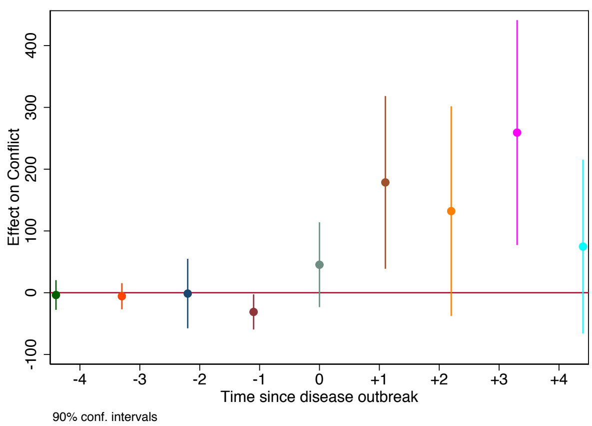
Figure A.4: Event study of Disease outbreaks on Conflict incidence

Outcome: Conflict events in year t





Conditional on civil liberties (above mean) × (1, disease outbreaks)

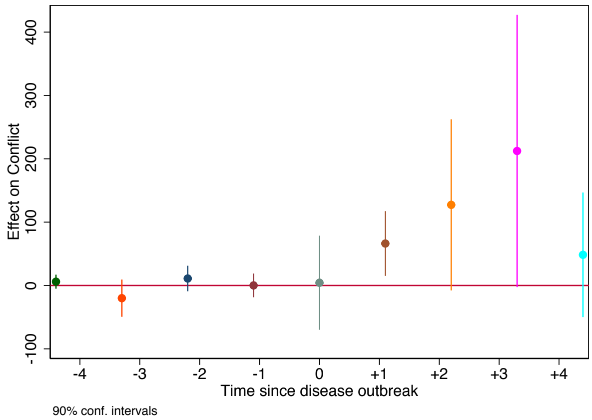


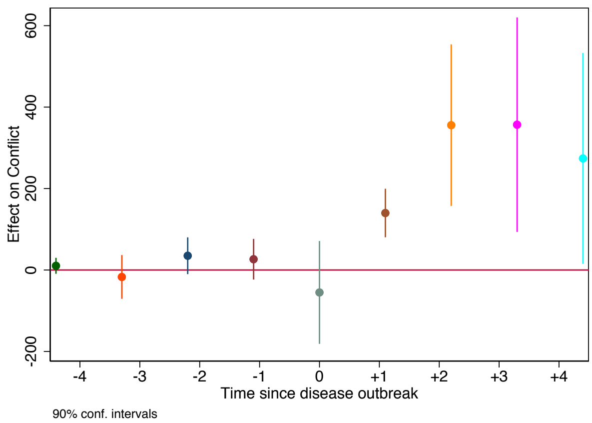
Conditional on political rights (above mean) × (1, disease outbreaks)

Notes: Conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD) at $(t-1)$, and disease outbreaks one year before and also at $(t-1)$. Weighted by average population over the sample period. For full specification equation (1.2). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). Disease-motivated conflicts according to the description of the event. Disease outbreak alerts (excluding updates) (WHO). Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico.

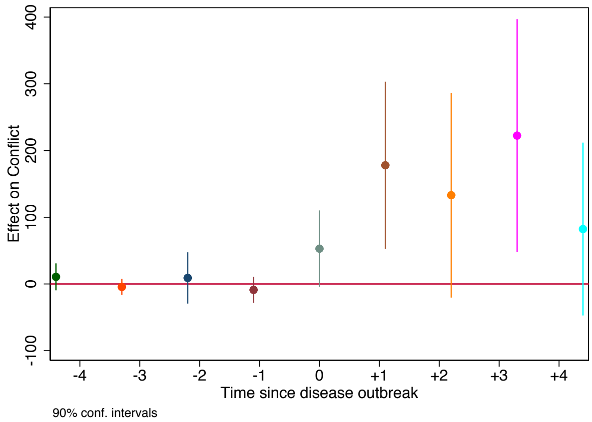
Figure A.5: Event study of Disease outbreaks on Riots

Outcome: Conflict events in year t





Conditional on civil liberties (above mean) × (1, disease outbreaks)

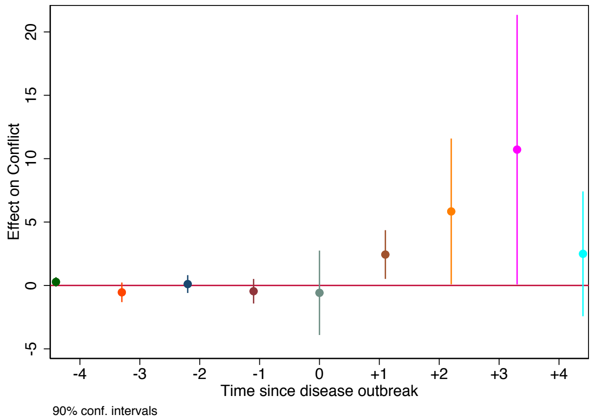


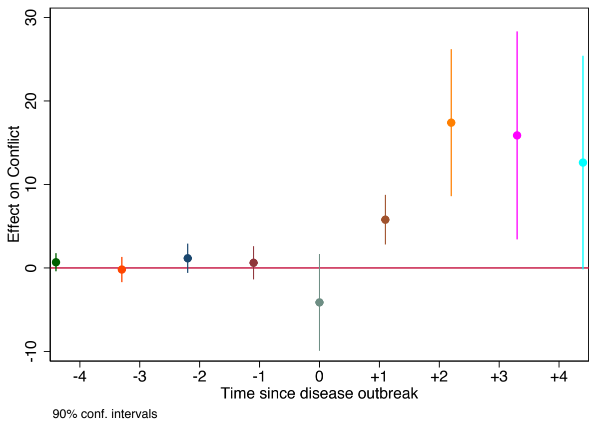
Conditional on political rights (above mean) × (1, disease outbreaks)

Notes: Conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD) at $(t-1)$, and disease outbreaks one year before and also at $(t-1)$. Weighted by average population over the sample period. For full specification equation (1.2). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). Disease-motivated conflicts according to the description of the event. Disease outbreak alerts (excluding updates) (WHO). Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico.

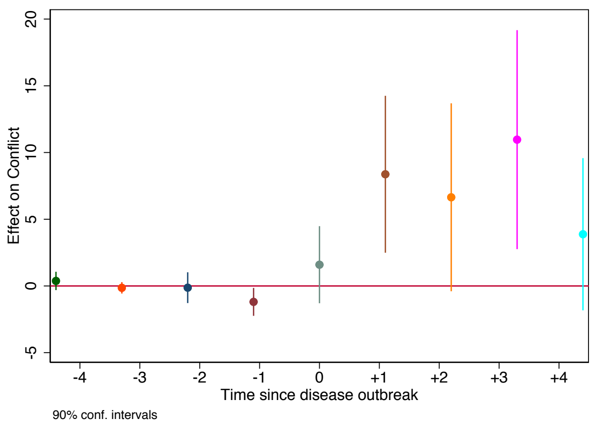
Figure A.6: Event study of Disease outbreaks on Health or Disease-related Conflict

Outcome: Conflict events in year t





Conditional on civil liberties (above mean) × (1, disease outbreaks)



Conditional on political rights (above mean) × (1, disease outbreaks)

Notes: Conditional on average population and GDP in 2010 constant US dollars (World Bank/OECD) at $(t-1)$, and disease outbreaks one year before and also at $(t-1)$. Weighted by average population over the sample period. For full specification equation (1.2). Definitions: *Conflicts*: average number of yearly Conflicts (ACLED). Disease-motivated conflicts according to the description of the event. Disease outbreak alerts (excluding updates) (WHO). Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico.

Table A.8: Event study on Riots by Civil Liberties (demeaned)

	Conflicts								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	3.738	-20.11	3.464	-5.104	13.57	69.72**	146.1*	231.2*	77.47
	(6.73)	(16.92)	(10.62)	(13.12)	(42.12)	(27.84)	(80.31)	(129.17)	(67.77)
disease(t) × Civil Liberties(t-1)	-0.988	-0.577	-2.528*	-1.304	4.180	4.387*	7.483*	7.440	14.53*
	(0.87)	(1.79)	(1.26)	(1.01)	(3.55)	(2.40)	(4.18)	(7.83)	(7.40)
Civil Liberties(t-1)	2.590	1.165	6.355	6.564	-11.56	9.778	-12.31	0.778	-56.14
	(2.43)	(3.28)	(7.44)	(8.99)	(25.37)	(41.32)	(23.96)	(30.62)	(52.53)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.567	0.484	0.560	0.548	0.897	0.887	0.875	0.878	0.896
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), disease(t+j-1), disease(t+j-1) × Covariate (t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Event study on Riots by Freedom of Expression (above mean)

	Conflicts								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	10.59	-25.53	24.83	16.41	-38.57	63.65	158.6*	270.2*	-28.01
	(10.63)	(29.01)	(22.57)	(25.44)	(92.51)	(49.89)	(82.31)	(140.37)	(101.34)
disease(t) × Freedom of Expression^{High}	-10.57	11.88	-28.07	-34.53	86.53	-16.13	-114.9	-114.5	81.94
	(10.10)	(25.32)	(24.51)	(29.70)	(115.01)	(65.35)	(71.93)	(223.00)	(77.93)
Freedom of Expression^{High}	5.677	-12.77	31.34	37.92	-122.5	296.0	793.9*	436.9*	675.4
	(16.94)	(30.90)	(24.06)	(28.42)	(150.39)	(178.54)	(456.10)	(222.53)	(455.26)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.562	0.484	0.551	0.546	0.897	0.888	0.882	0.878	0.899
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), disease(t+j-1), disease(t+j-1) × Covariate (t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Event study on Riots by Freedom of Expression (demeaned)

	Conflicts								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	4.311	-19.48	5.603	-8.586	33.77	57.59	57.76	160.0	-90.40
	(6.91)	(17.28)	(11.37)	(13.48)	(46.51)	(56.90)	(81.80)	(137.41)	(103.44)
disease(t) × Freedom of Expression(t-1)	-4.873	0.389	-8.891**	-7.798*	22.96	-12.70	-6.104	-33.36	48.84
	(3.85)	(7.74)	(4.23)	(4.48)	(32.29)	(24.20)	(12.74)	(20.21)	(43.23)
Freedom of Expression(t-1)	7.204*	3.365	16.41	25.72	-17.97	68.29	87.59	171.9	165.1
	(4.13)	(7.94)	(11.43)	(19.41)	(93.69)	(137.62)	(90.50)	(202.88)	(219.97)
Observations	416	469	522	522	522	471	420	369	318
R-squared	0.571	0.484	0.560	0.573	0.903	0.893	0.881	0.889	0.908
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), disease(t+j-1), disease(t+j-1) × Covariate (t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: Event study on Riots by Health Expenditure (above mean)

	Conflicts								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	0.739	-15.84	-0.179	9.309	-51.09	-0.829	179.6*	167.5*	228.3**
	(9.20)	(13.01)	(16.41)	(11.03)	(47.63)	(22.62)	(103.57)	(84.44)	(91.87)
disease(t) × Health Expenditure^{High}	6.675	-6.408	17.20	-16.09	124.5	184.3	-116.9	68.80	-482.2***
	(11.39)	(34.49)	(14.51)	(24.18)	(102.31)	(121.76)	(110.28)	(156.33)	(177.63)
Health Expenditure^{High}	4.356	17.81	12.20	47.75	-169.7	-303.9	367.1	349.1*	1026.8**
	(8.29)	(27.73)	(15.64)	(28.58)	(138.67)	(198.55)	(279.62)	(184.98)	(427.05)
Observations	416	469	522	575	628	577	526	475	424
R-squared	0.561	0.485	0.551	0.549	0.897	0.889	0.878	0.879	0.911
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), disease(t+j-1), disease(t+j-1) × Covariate (t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: Event study on Riots by Health Expenditure (demeaned)

	Conflicts								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	6.385	-13.62**	8.265	-10.63*	-2.401	74.04**	144.5	197.4	65.10
	(7.31)	(6.49)	(18.19)	(6.13)	(8.86)	(32.31)	(87.19)	(125.25)	(52.69)
disease(t) × Health Exp.(t-1)	-1.602	5.880	-1.261	-3.129	0.844	-14.88	-51.80	73.47	-70.95
	(5.32)	(5.26)	(9.43)	(6.95)	(4.95)	(21.01)	(34.27)	(100.74)	(68.67)
Health Exp.(t-1)	7.995	6.297	13.17	5.863	-11.36	53.75	41.43	43.55	141.6
	(7.84)	(5.94)	(10.80)	(11.54)	(14.61)	(67.14)	(101.56)	(72.10)	(99.78)
Observations	365	418	471	524	577	577	526	475	424
R-squared	0.498	0.571	0.483	0.555	0.536	0.887	0.875	0.877	0.894
Mean	18.92	27.57	34.33	45.36	395.4	427.6	465.3	511.3	567.2

(Robust SE), Time-FE, Country-FE, Year*Continent FE,
Controls: Population (t-1), GDP (t-1), disease(t+j-1), disease(t+j-1) × Covariate (t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.13: Event study of Disease outbreaks on Conflict - Count Data Model

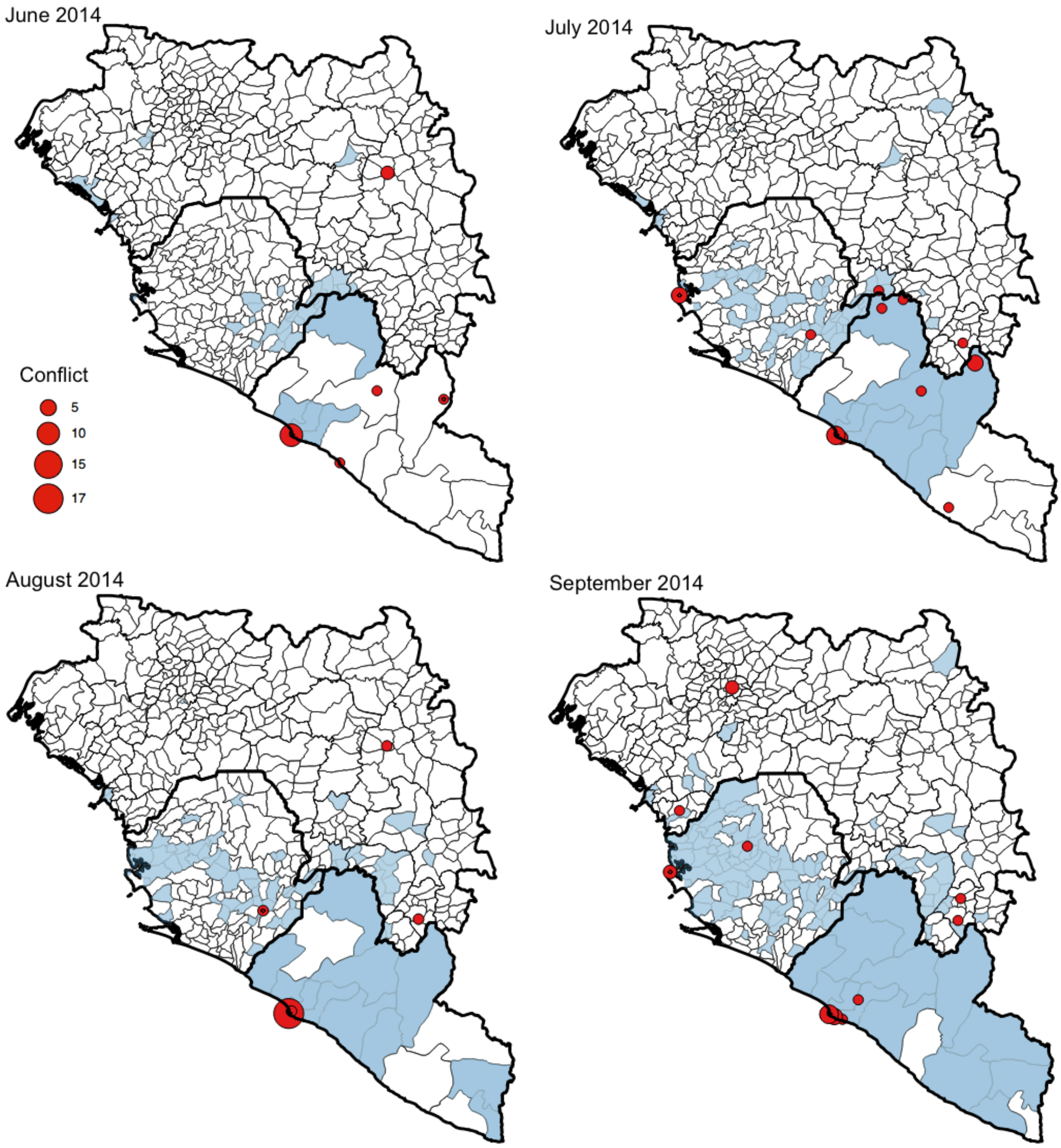
	Conflicts								
	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
disease(t)	0.0270	-17.56	18.24	-16.39	-57.39	-36.22	150.7*	259.7	106.4
	(6.05)	(19.18)	(15.50)	(20.41)	(92.42)	(54.49)	(79.21)	(175.84)	(150.00)
Observations	416	469	522	575	628	577	526	475	424

(Robust SE), Time-FE, Country-FE
Controls: Population (t-1), GDP (t-1), Disease(t+j-1), Disease(t-1)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows marginal effects at the average level of disease outbreaks in a Poisson regression model estimated by Maximum Likelihood.
Observations: 66 countries over 2004-2016 in Africa, South and South East Asia, Central America, the Caribbean and Mexico (excluding Pakistan, Somalia and South Sudan).

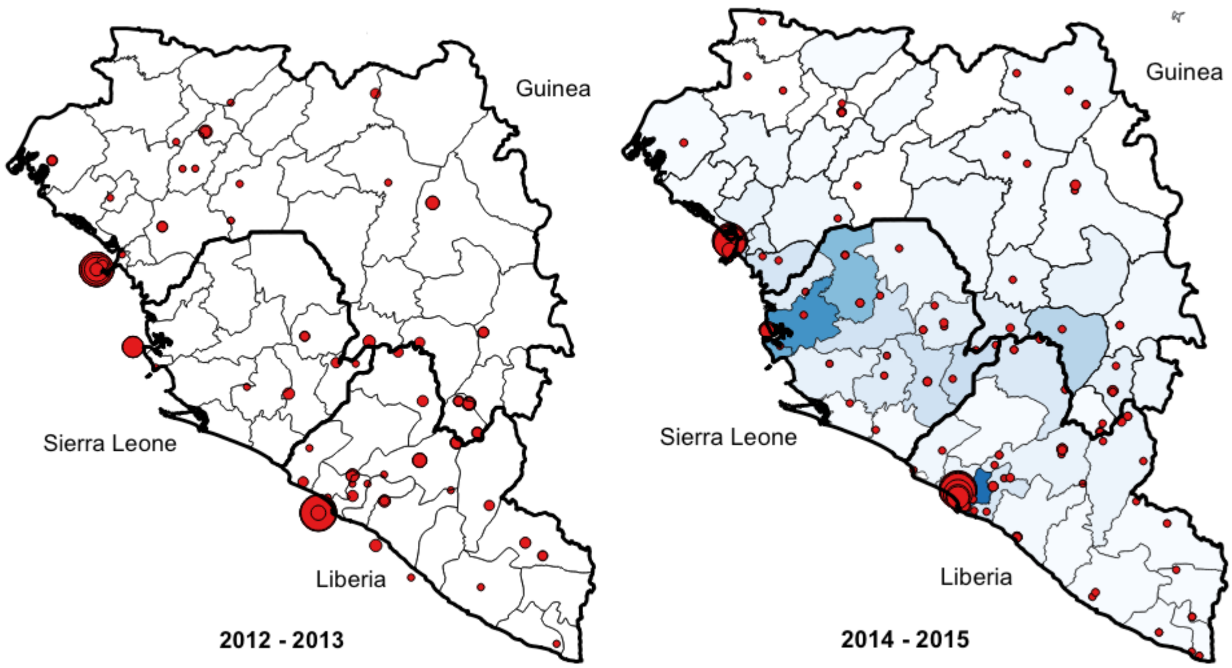
B Appendix to Chapter 2

Figure B.1: Presence of the epidemic and conflict incidence month per month



Notes: Presence of the epidemic $\in \{0, 1\}$ (blue shade) and number of conflicts in a given location month per month (red dots).

Figure B.2: Total Ebola and Conflict incidence in West Africa, pre and post-Epidemic



Notes: Cumulative Ebola infections per district (more if darker shade) and Conflict events (red dots) weighted by number of conflicts in the same location. We see more conflict events in Sierra Leone in the post-Epidemic compared to pre-Epidemic period. We see some displacement of conflict in Guinea towards locations with more cumulative number of Ebola infections. For Liberia the effects are not evident from the raw data at cross-sectional level.

Figure B.3: Aggregate number of Ebola cases (confirmed + probable)

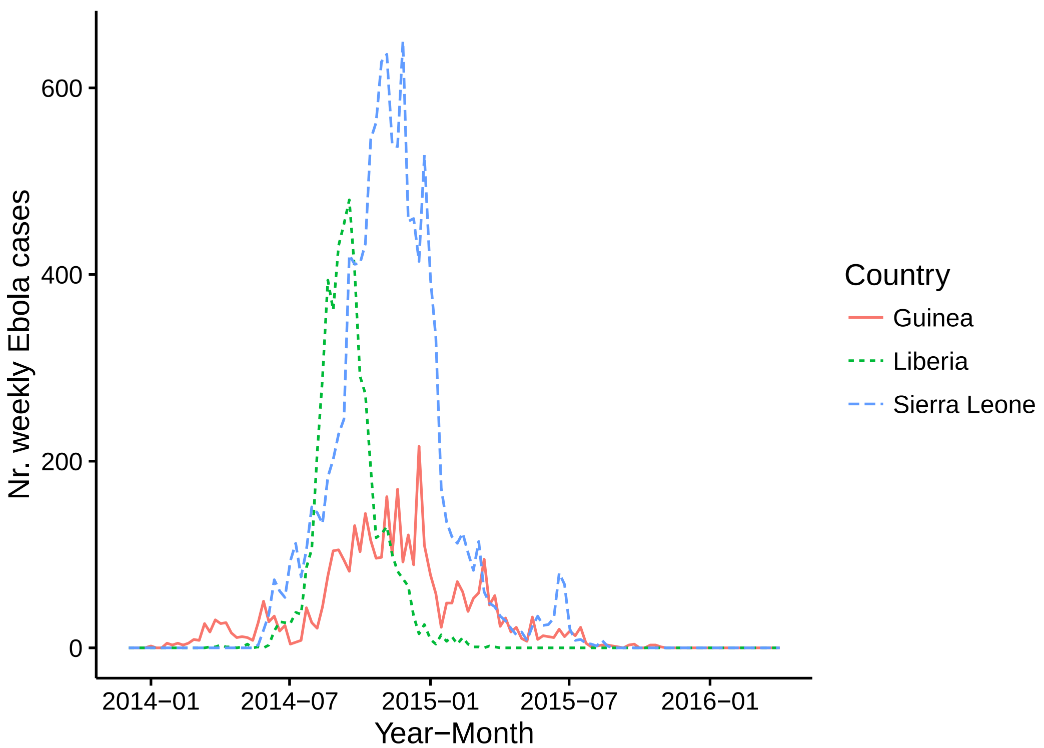


Figure B.4: Density of Riots and Protests in affected countries (above) or all Africa (below), 2010-2016

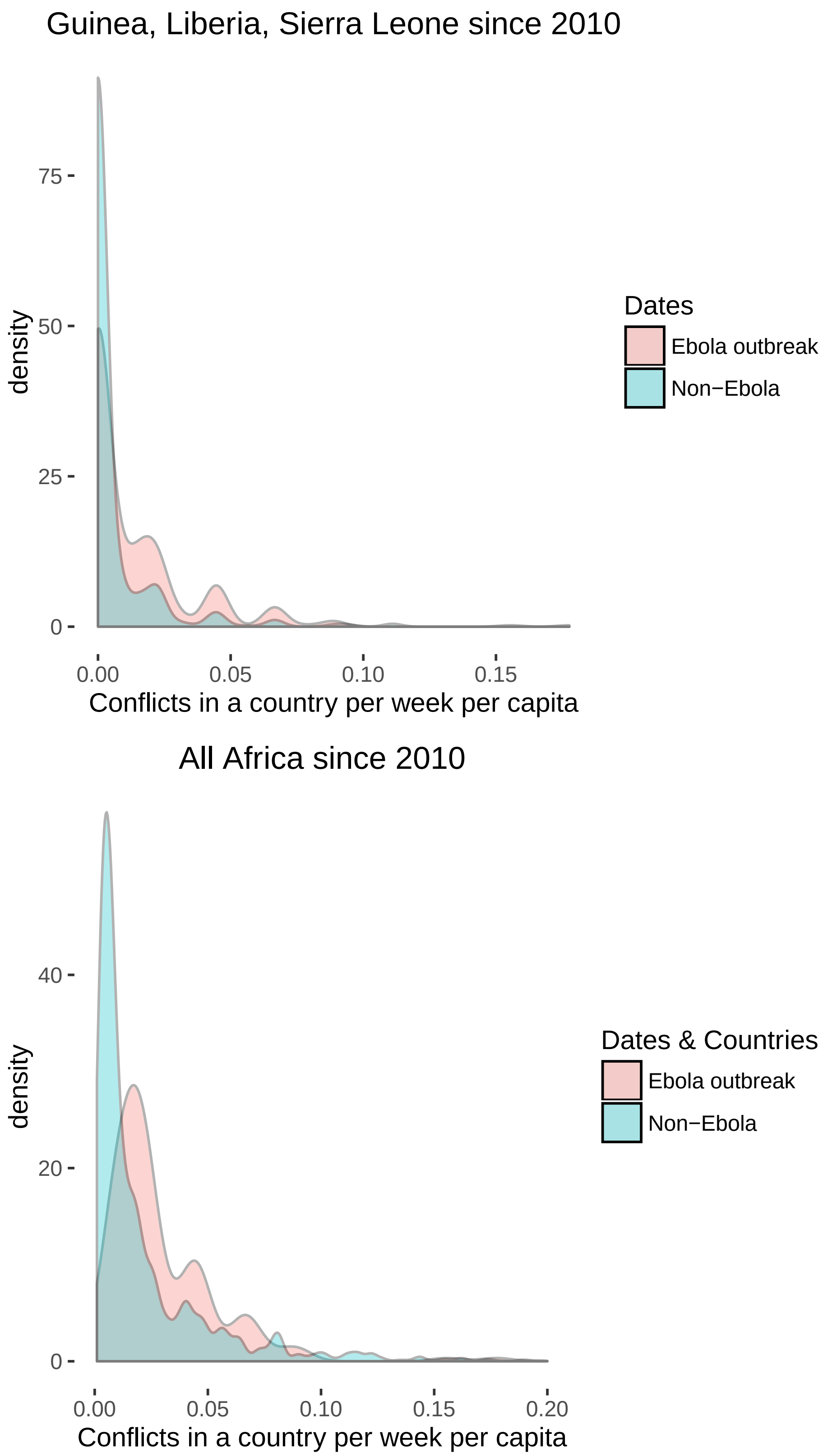


Table B.1: Descriptives in Yearly quarters from Jan 2012 to May 2016

	Pre-Epidemic 2012-2013	Post-Epidemic 2014-2016/Q2	Total	Difference Post-Pre Epid [t-test]	Total
Conflict	0.0383	0.0534	0.0467	0.0151	
	(0.393)	(0.539)	(0.479)	[1.61]	
conflict	0.763	0.856	0.815	0.0929	
	(8.641)	(7.904)	(8.239)	[0.57]	
EbolaTotal					66.83
					(283.0)
ebolaTotal					50.08
					(124.9)
Observations	4,672	5,840	10512		584

Notes: The epidemic starts at the end of December 2013 in Guinea, but we do not observe the first few cases. $Conflict$ is the number of conflicts in a given yearly quarter (riots, protests and violence against civilians) for each observational unit. $conflict$ is the number of conflict events in one million per capita in a yearly quarter. Difference in means post-Epidemic-pre-Epidemic are followed by t-test statistics in square brackets. $EbolaTotal$ are the total cumulative number of Ebola cases counted at the end of the epidemic. $ebolaTotal$ are these measured in 100'000 per capita.

Table B.2: Summary statistics

Ebola cases	Pre-Epid. 2012-13	Epidemic 2014-16/5	Total 2012-16	**Conflict**	Pre-Epid. 2012-13	Epidemic 2014-16/5	Total 2012-16	Difference Epid.-Pre-Epid.
ebola $\in \{0,1\}$	0	0.071	0.039					
	(0)	(0.257)	(0.19)					
confirmed	0	0.815	0.447					
	(0)	(9.631)	(7.140)					
probable	0	0.245	0.134	conflict $\in \{0,1\}$	0.00491	0.00679	0.00594	0.00189**
	(0)	(3.897)	(2.887)		(0.0699)	(0.0822)	(0.0768)	[3.17]
ebola (c+p)	0	1.061	0.581					
	(0)	(12.88)	(9.55)	Conflicts	0.00589	0.00848	0.00731	0.00259**
ebola^{pc} (c+p)	0	0.855	0.468		(0.0914)	(0.116)	(0.106)	[3.16]
	(0)	(7.49)	(5.56)					
suspect	0	1.662	0.911	**Conflicts**^{pc}	0.117	0.136	0.128	0.0185
	(0)	(15.26)	(11.33)		(0.279)	(2.85)	(2.82)	[0.84]
total	0	2.723	1.492					
	(0)	(22.59)	(16.78)					
ebola^{pc} total	0	1.553	0.851					
	(0)	(10.06)	(7.485)					
N	30,368	36,792	67160	N	30,368	36,792	67160	
chiefdom (SLE) / sub-pref (GIN) / county (LBR)				chiefdom (SLE) / sub-pref (GIN) / district(LBR)				
2-week windows				2-week windows, * p<0.05, ** p<0.01, (SE), [t-stat]				

Notes: The main variables used in the regressions are $Conflicts^{pc}$, namely the number of conflicts in one million per capita and $ebola^{pc}$ (c+p), the number of confirmed and probable Ebola cases in 100'000 per capita.

Table B.3: Descriptives - State Response - provision by country (population-weighted)

	GIN	LBR	SLE	Total
EverETU	0.135	0.512	0.224	0.238
	(0.342)	(0.503)	(0.418)	(0.426)
EverLab	0.126	0.451	0.293	0.242
	(0.333)	(0.500)	(0.457)	(0.429)
EverCCC	0.133	0.190	0.620	0.294
	(0.340)	(0.394)	(0.487)	(0.456)
EverQuar	0.0290	0.825	0.762	0.412
	(0.168)	(0.382)	(0.428)	(0.493)
NearETU^{end}	0.133	0.500	0.186	0.223
	(0.338)	(0.490)	(0.385)	(0.411)
NearLab^{end}	0.123	0.445	0.256	0.228
	(0.323)	(0.494)	(0.435)	(0.415)
Observations				584

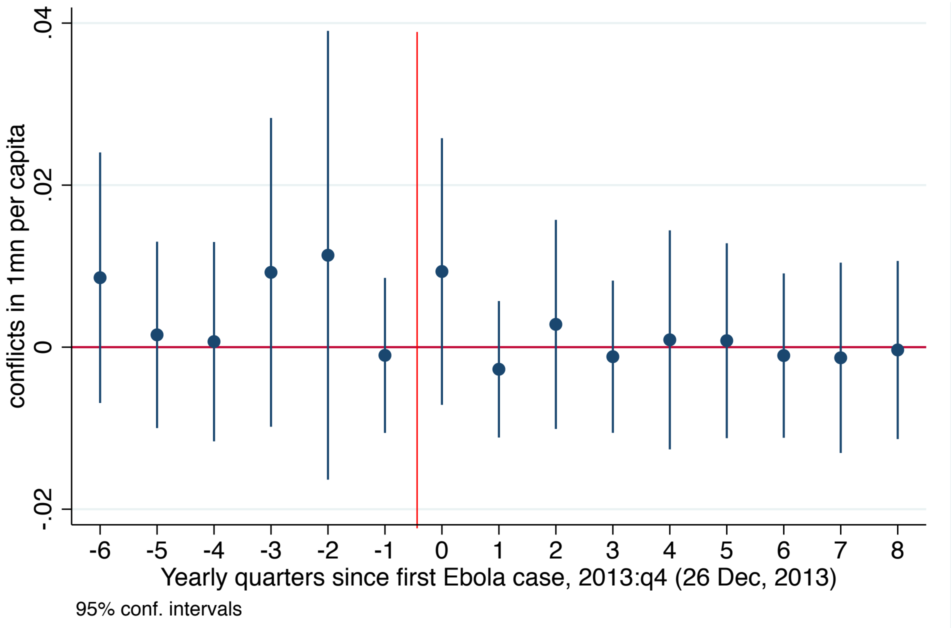
Notes: Ebola treatment Units (ETU), Laboratories, Community care centers (CCCs), Military district-Quarantines. *Ever* are dummy variables indicating whether a location had access to it or not. $Near^{end}$ is the smallest inverse distance to an ETU/Lab measured at the end of the outbreak for locations that do not have one on their own, or 0 if they do.

Table B.4: Descriptives - State Response - average population size

	ETUs	Labs	CCCs	Quarantines
Without	31,512	31,205	35,642	33,503
	(51656.8)	(51016.4)	(97315.7)	(62999.3)
With	175,189	190,972	51,227	51,487
	(349568.5)	(358544.7)	(105232.8)	(150396.6)
Total	39,138	39,138	39,138	39,138
	(99267.3)	(99267.3)	(99267.3)	(99267.3)
Observations	584	584	584	584

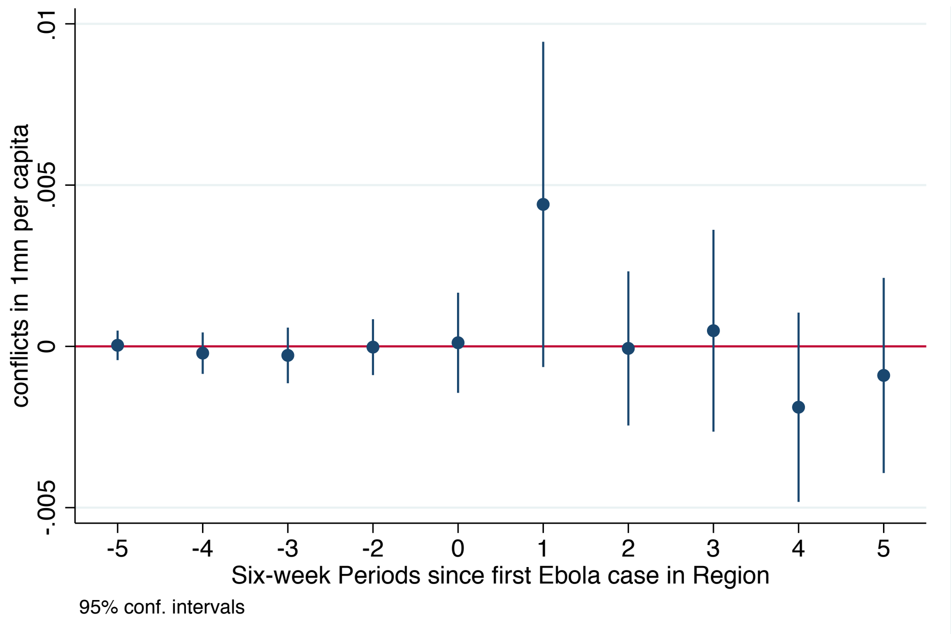
Notes: Ebola treatment Units (ETU), Laboratories, Community care centers (CCCs), Military district-Quarantines or area blockades.

Figure B.5: Difference in Difference relative to the first case in country - Guinea



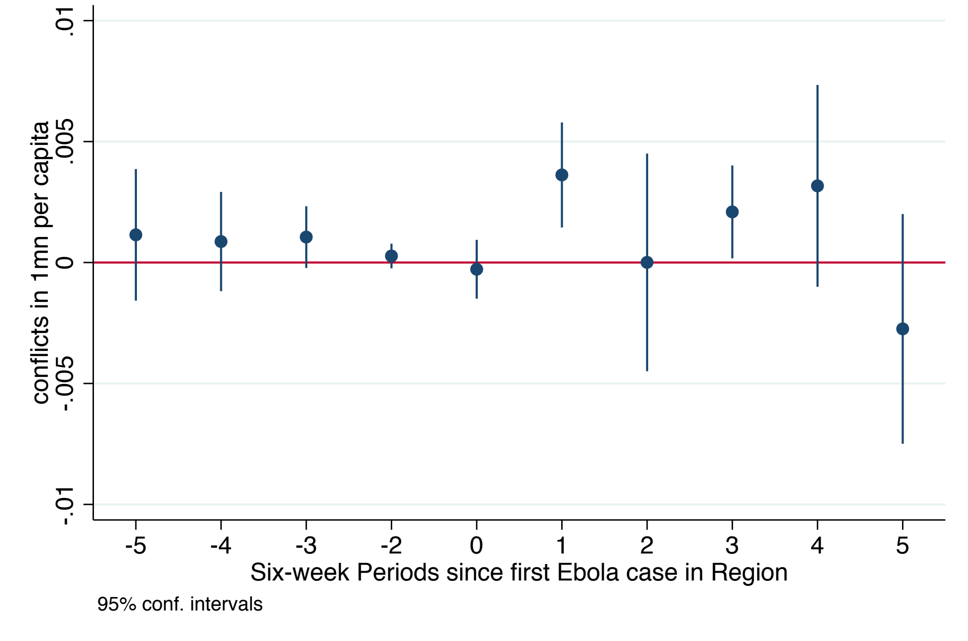
Notes: Coefficients on the total end-number of Ebola cases in 100'000 per capita in a given location (sub-prefecture) × dummy for a yearly quarter. Calendar time since first case in Guinea. Omitted category: 2012:q1.

Figure B.6: Difference in Difference relative to first case in prefecture - Guinea



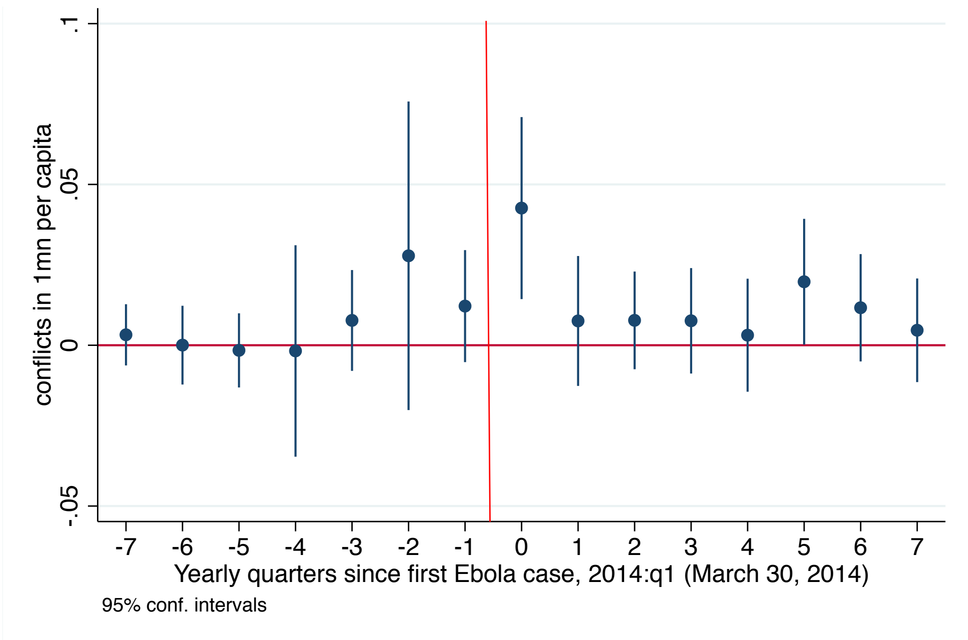
Notes: Coefficients on the total end-number of Ebola cases in 100'000 per capita in a given location (sub-prefecture) × dummy for a six-week period. Time relative to first case in region (prefecture). Omitted category: period -1.

Figure B.7: Difference in Difference relative to first case in district - Sierra Leone



Notes: Coefficients on the total end-number of Ebola cases in one location (chiefdom) $\times$ dummy for a six-week period. Time relative to first case in region (district). Omitted category: period -1.

Figure B.8: Difference in Difference relative to the first case in country - Liberia



Notes: Coefficients on the total end-number of Ebola cases in one location (county) $\times$ dummy for a yearly quarter. Calendar time since first case in Liberia. Omitted category: 2012:q1.

Table B.5: Difference in Differences relative to the first index case in West Africa - First Stage

	First Stage	Reduced Form
	(1)	(2)
	ebolaTot × PostEbola	conflict(quarter)
DistEpic × PostEbola	-.00101***	-1.11e-06
	(.000369)	(3.40e-06)
DistEpic × I(Guinea) × PostEbola	.000388	-6.00e-08
	(.000283)	(2.46e-06)
DistEpic × I(Liberia) × PostEbola	.0014***	.000013
	(.000427)	(7.90e-06)
DistEpic^2 × PostEbola	3.77e-09***	6.92e-12
	(1.07e-09)	(9.44e-12)
DistEpic^2 × I(Guinea) × PostEbola	-2.92e-09***	-7.93e-12
	(9.70e-10)	(8.72e-12)
DistEpic^2 × I(Liberia) × PostEbola	-5.26e-09***	-2.82e-11
	(1.22e-09)	(1.97e-11)
N	10512	10512
R2	0.706	0.429
Time FE	Y	Y
Chiefd FE	Y	Y

(Clustered SE) by Dist; Controls Restr.: sample restricted to locations with household survey data.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: $conflict$ is the number of conflicts in each yearly quarter in 1 million per capita. $ebolaTotal$ is the total cumulative number of Ebola cases measured at the end of the outbreak for each location in 100'000 per capita. $PostEbola$ is a post-treatment dummy taking value 1 from 2014 on, after the first Ebola case is observed. $DistEpic$ is the geographic linear distance to the first index case, $DistEpic^2$ is the square distance. $I(.)$ is an indicator variable for each country.
First stage F-Statistic: 10.24.

Table B.6: Distance to the Epicenter does not predict Conflict incidence pre-epidemic (stand. coef)

	(1) conflict(t)	(2) Ethnic Fract.	(3) Ethnic Polar.	(4) Ethnic Salience	(5) Strongly Relig.	(6) Trad. Relig.	(7) Trust Leader	(8) Trust People	(9) Infrastr.	(10) Incumbent Vote/Pref.
DistEpic	0.047	0.567	-0.308	0.305	0.464	-1.033**	-0.240	-0.466	0.226	-0.558*
	[1.40]	[1.22]	[-0.92]	[0.70]	[1.40]	[-2.39]	[-0.80]	[-1.23]	[1.42]	[-1.89]
DistEpic^2	-0.024	-0.393	0.388	-0.143	-0.312	0.751**	0.671**	0.511	-0.268	0.615**
	[-0.51]	[-0.81]	[1.18]	[-0.33]	[-1.03]	[2.07]	[2.35]	[1.28]	[-1.27]	[2.27]
N	30368	215	215	215	215	215	215	215	215	215
R2	0.006	0.046	0.015	0.029	0.033	0.135	0.197	0.019	0.006	0.028

Standardized coef.; [t-stat]; Robust SE clustered by Location; Week FE

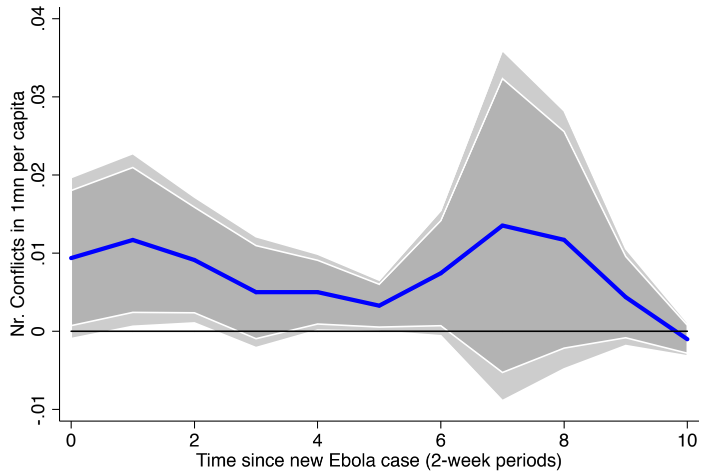
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: In column (1) t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $DistEpic$ is the geographic linear distance to the first index case, $DistEpic^2$ is the square distance. Columns (2)-(10) measure the correlation between these and expected correlates of civil violence based on survey data from the Afrobarometer round immediately prior to the epidemic, 2012-13.

Table B.7: Descriptives - Population by country for each observational unit

	(1) all	(2) ebola
Guinea	33,119	
	(66387.9)	
Liberia	49,592	267,264.6
	(173878.1)	(294331.4)
Sierra Leone	46,361	
	(98821.1)	
Total	39,138	
	(99267.3)	
Observations	584	499

Figure B.9: Impulse response for local projections for the impacts of ebola infections in 100'000 per capita (intensive margin) on conflict incidence for 10 future time periods



Notes: The coefficients of $ebola_{t-1}$ in equation (2.5) are plotted, with 90% and 95% confidence intervals. We condition on 9 lags in ebola and conflict (two-week frequency).

Table B.8: High-frequency panel: Main specification

Outcome: conflict(t)	Pooled	Panel					
	(1)	(2)	(3)	(4)	**(5)**	**(6)**	**(7)**
ebola(t-1)	0.0173***	0.0138***	0.0129***	0.0116**	**0.0146******	**0.0141******	**0.0123*****
	(0.0047)	(0.0039)	(0.0038)	(0.0049)	(0.0041)	(0.0039)	(0.0049)
ebola(t-2)				0.00195			0.00290
				(0.0041)			(0.0043)
ebolaCum(t-2)			0.000492**	0.000452*		0.000464*	0.000401
			(0.0002)	(0.0003)		(0.0003)	(0.0003)
Constant	0.176***						
	(0.0503)						
N	66576	66576	65992	65992	66574	65990	65990
R2	0.002	0.125	0.126	0.126	0.143	0.144	0.144
Time FE		Y	Y	Y	Y	Y	Y
Chiefd FE		Y	Y	Y	Y	Y	Y
Reg × Month FE					Y	Y	Y

(Clustered SE) by Dist

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. *ebola* is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of Ebola infections over time. Our preferred specifications and our coefficient of interest are highlighted in bold.

Table B.9: Main specification - High frequency panel (standardized coef.)

Outcome: conflict(t)	Pooled	Panel					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ebola(t-1)	0.046***	0.037***	0.035***	0.031**	0.039***	0.038***	0.033**
	(0.0047)	(0.0039)	(0.0038)	(0.0049)	(0.0041)	(0.0039)	(0.0049)
ebola(t-2)				0.005			0.008
				(0.0041)			(0.0043)
ebolaCum(t-2)			0.013**	0.011*		0.012*	0.010
			(0.0002)	(0.0003)		(0.0003)	(0.0003)
N	66576	66576	65992	65992	66574	65990	65990
R2	0.002	0.125	0.126	0.126	0.143	0.144	0.144
Time FE		Y	Y	Y	Y	Y	Y
Chiefd FE		Y	Y	Y	Y	Y	Y
Reg × Month FE					Y	Y	Y

Stand. coef.; (Clustered SE) by Dist

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of Ebola infections over time. Our preferred specifications and our coefficient of interest are highlighted in bold.

Table B.10: Difference-in-Difference using first index case in each location

Outcome: conflict(t)	Pre-Trends?		Diff-in-Diff				
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) 2SLS
ebolaTot × PostEbola × Trend	0.00000681	0.00000681					
	(0.000005)	(0.000005)					
ebolaTot × Trend	0.00000171	0.00000171			-0.00000425	-0.00000338	
	(0.000007)	(0.000007)			(0.000005)	(0.000006)	
PostEbola			0.0630				
			(0.061905)				
PostEbola × ebolaTot				0.000889***	0.00113***	0.00116**	0.00121***
				(0.000266)	(0.000429)	(0.000573)	(0.000396)
N	67160	67160	67160	67160	67160	67158	67160
R2	0.124	0.124	0.123	0.124	0.124	0.142	0.124
Time FE	Y	Y	Y	Y	Y	Y	Y
Chiefd FE	Y	Y	Y	Y	Y	Y	Y
Reg × Month FE		Y				Y	

(Clustered SE) by Location

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebolaTot$ is the total end-number Ebola cases in 100'000 per capita. $ebolaPost$ is a dummy variable that is 0 before Ebola hits a location for the first time and then takes value 1 forever. In the last column we instrument $ebolaPost \times ebolaTot$ with the geographic linear and square distance to epicenter, interacted with $ebolaPost$ and country-dummies. First stage: $R^2 = 0.66$, $F - statistic = 12.93$.

Table B.11: High frequency panel - Instrument : $ebolaNeigh(t-2) \in \{0,1\}$

	OLS	2SLS		Reduced Form	First Stage
	(1) conflict(t)	(2) conflict(t)	(3) conflict(t)	(4) conflict(t)	(5) ebola(t-1)
ebola(t-1)	0.0138***	0.0377***	0.0374***		
	(0.0039)	(0.0123)	(0.0124)		
conflictOthers(t-2)			0.0916		
			(0.0690)		
ebolaNeigh(t-2) × $I(Liberia)$				0.203	3.526***
				(0.1223)	(1.1462)
ebolaNeigh(t-2) × $I(SierraLeone)$				0.162**	4.596***
				(0.0692)	(0.8478)
ebolaNeigh(t-2) × $I(Capital)$				0.0466	1.919
				(0.1569)	(1.1676)
ebolaNeigh(t-2) × $I(District-Capital)$				-0.000360	3.765***
				(0.0934)	(1.0700)
N	66576	65992	65992	65992	65992
R2	0.125	0.123	0.123	0.125	0.192
Time FE	Y	Y	Y	Y	Y
Chiefd FE	Y	Y	Y	Y	Y

(Clustered SE) by Dist

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: $conflict(t)$ are the number of conflicts in one million per capita in the own location. $conflictOthers(t-2)$ is the number of conflict events in the region except the own location. $ebola(t-1)$ is the number Ebola cases in 100'000 per capita. The instrument is the presence of the epidemic in neighboring locations, $ebolaNeigh(t-2) \in \{0,1\}$. We allow for the effect to vary for each country, as well as the capital and main chiefdoms within a given district, using indicator variables $I(.)$. First stage: $R^2 = 0.19, F-Statistic = 40.26$.

Figure B.10: Predicted Ebola vs Ebola cases in Sierra Leone following Fang et al. (2016)

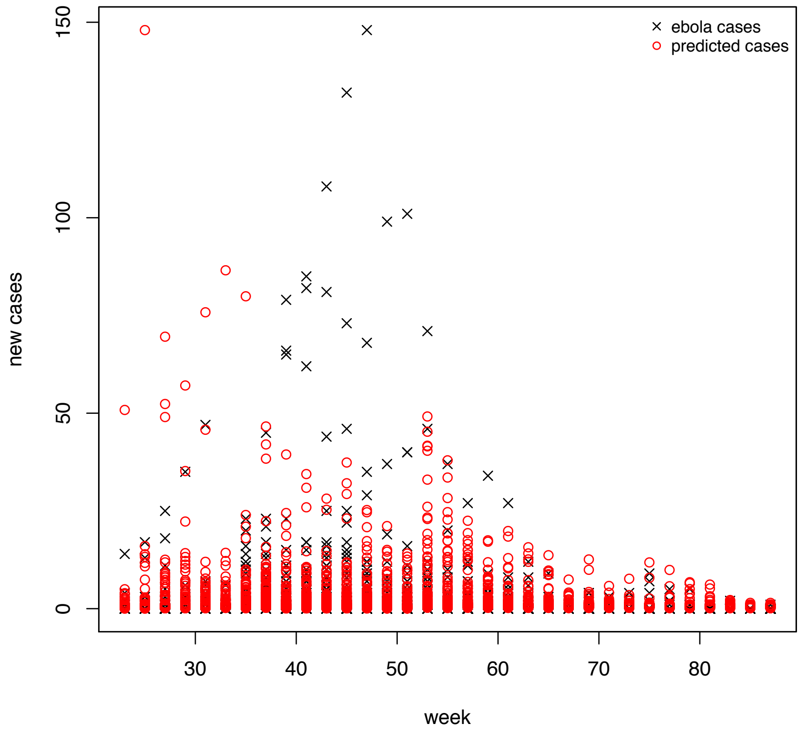


Table B.12: Lags and Leads (regression)

	(1) conflict(t)
ebola(t)	0.00775
	(0.00605)
ebola(t-1)	**0.00566****
	(0.00230)
ebola(t-2)	0.00184
	(0.00567)
ebola(t-3)	0.00309
	(0.00383)
ebola(t+1)	-0.00165
	(0.00496)
ebola(t+2)	0.00534
	(0.00351)
ebola(t+3)	0.00447
	(0.00296)
ebolaCum(t-3)	0.000539***
	(0.000175)
N	63652
R2	0.147

(Clustered SE) by Dist; Time FE, Chiefd. FE; Reg. × Month FE
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of Ebola infections over time.

Table B.13: Lags and Leads (F-test)

	(1) p-value
ebola(t-1)=ebola(t)	0.724
ebola(t-1)=ebola(t-2)	0.594
ebola(t-1)=ebola(t-3)	0.540
ebola(t-1)=ebola(t+1)	0.242
ebola(t-1)=ebola(t+2)	0.946
ebola(t-1)=ebola(t+3)	0.763
(Lags)=0	**0.000**
SumLags=0	**0.000**
(Leads t+1, t+2)=0	0.320
SumLeads t+1, t+2=0	0.489
(LeadsAll)=0	0.271
SumLeadsAll=0	0.165

Stand. coef.; (Clustered SE) by Dist; Time FE, Chiefd. FE; Reg. × Month FE
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: F-test in a regression including new Ebola cases at three leads and lags and controlling for cumulative Ebola, Table B.12. t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. *ebola* is the number Ebola cases in 100'000 per capita. *ebolaCum* is the cumulative number of Ebola infections over time.

Table B.14: Wooldridge (2002) test for autocorrelation in Panel data

Linear model: $conflict$ on *ebola*, *ebolaCum*

H_0: no first-order autocorrelation	
F(1, 583)	0.056
p-value	0.8130

Notes: The specification is in two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. *ebola* is the number Ebola cases in 100'000 per capita. *ebolaCum* is the cumulative number of cases over time in 100'000 per capita.

Table B.15: Feedback effects?

	conflict(t)					ebola(t)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ebola(t-1)	0.0137***	0.0121***	0.0128***	0.0114***		0.636***	0.630***
	(0.0043)	(0.0040)	(0.0040)	(0.0037)		(0.0948)	(0.1076)
ebolaCum(t-1)		0.000684***		0.000645***			
		(0.0002)		(0.0002)			
conflict(t-1)			0.0534	0.0532	0.0545		0.00738
			(0.0410)	(0.0410)	(0.0409)		(0.0103)
conflict(t-1) × ebola(t-1)							0.00127
							(0.0039)
N	66576	66576	66576	66576	66576	66576	66576
R2	0.142	0.142	0.144	0.144	0.143	0.605	0.605

(Clustered SE) by Dist; cond. Time, Chiefd, Reg × Month FE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of cases over time in 100'000 per capita.

Table B.16: Robustness: different Conflict and Ebola measures

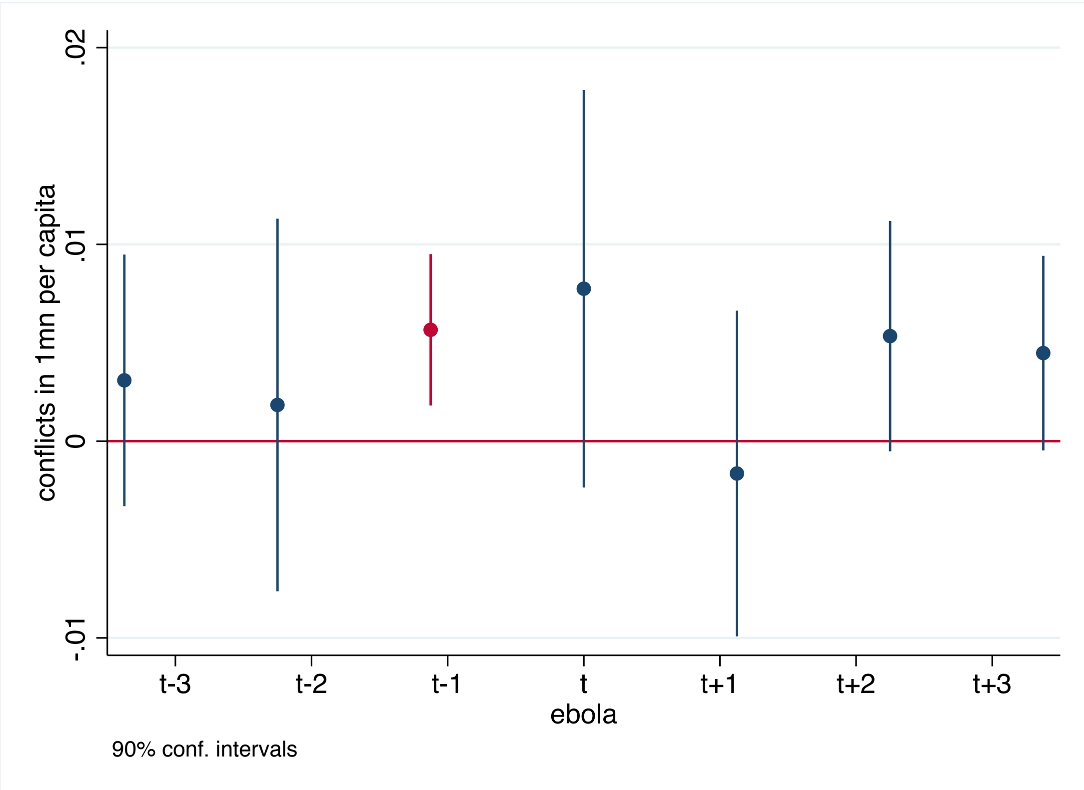
	(1) conflict(t)	(2) conflict(t) $\in \{0,1\}$	(3) conflict(t)	(4) conflict(t) $\in \{0,1\}$
ebola(t-1)	0.00208***	0.000907***		
	(0.00031)	(0.00003)		
ebola+suspect(t-1)			0.00145***	0.000657***
			(0.00023)	(0.00010)
Mean	0.10	0.01	0.10	0.01
N	66576	66576	66576	66576
R2	0.12	0.55	0.12	0.55

(Clustered SE) by Chiefd/County; Time FE, Chiefd FE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $conflict \in \{0,1\}$ indicates whether there has been any conflict or not in a given period. $ebola$ is the number Ebola cases in 100'000 per capita. $ebola + suspect$ is the number Ebola cases including suspect cases in 100'000 per capita.

Figure B.11: Lags and Leads (graph)



Notes: Coefficients on *ebola* at different time periods in a regression including new Ebola cases at three leads and lags and controlling for cumulative Ebola, Table B.12. t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of Ebola infections over time.

Table B.17: Robustness: Linear Probability Model vs Count Data Model (Marginal effects)

Outcome: conflict $\in \{0,1\}$	Linear Prob.			Poisson	
	(1)	(2)	(3)	(4)	(5)
ebola(t-1)	0.00476*	0.00241*	0.00212**	0.000773	0.000818***
	(0.0028)	(0.0013)	(0.0009)	(0.0005)	(0.0002)
ebola(t-2)			0.000880		0.000164
			(0.0010)		(0.0004)
ebolaCum(t-2)			0.0000761		0.0000616
			(0.0001)		(0.0001)
N	66576	66576	65992	66576	65992
Chiefd FE		Y			
Population			Y		Y

(Clustered SE) by Chiefd/County.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict \in \{0,1\}$ indicates whether there has been any conflict or not in a given period. *ebola* is the number Ebola cases in 100'000 per capita. *ebolaCum* is the cumulative number Ebola cases in 100'000 per capita. *Population* is the population. Columns (1)-(3) show coefficients of a linear probability model estimated by OLS. Columns (4)-(5) show marginal effects at the average level of $ebola(t-1)$ of a Poisson regression model estimated by Maximum Likelihood.

Table B.18: Spillovers in conflict incidence?

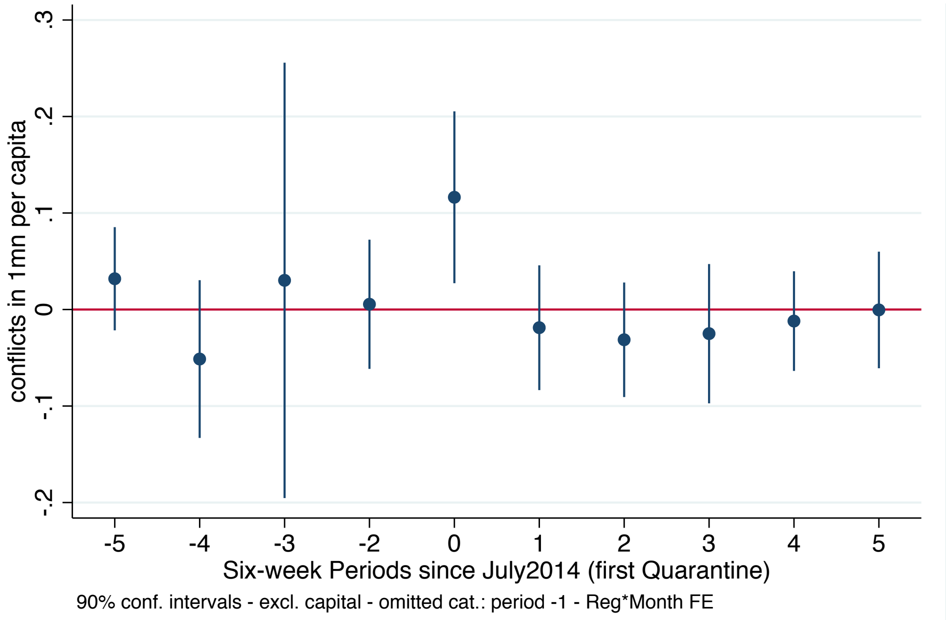
	Conflict Others		Conflict Others pre-Ebola	Neighb Ebola		
	(1) conflict(t)	(2) conflict(t)	(3) conflict(t)	(4) conflict(t)	(5) conflict(t)	(6) conflict(t)
conflict-Others(t)	5271.1					
	(3501.3081)					
conflict-Others(t-1)		592.3	1285.1			
		(861.2889)	(2718.6160)			
ebolaCum-Neighb(t-1)				0.0000296		
				(0.0000)		
ebola-Neighb(t-1)					0.000681	
					(0.0009)	
ebola-Neighb(t-1) $\in \{0, 1\}$						0.0920
						(0.0678)
N	67160	66576	29784	66576	66576	66576
R2	0.124	0.124	0.172	0.124	0.124	0.124
Time FE	Y	Y	Y	Y	Y	Y
Chiefd FE	Y	Y	Y	Y	Y	Y

(Clustered SE) by Dist

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $conflictOthers$ is the presence of conflict in the region except the own. $ebola - Neighb$ is the number Ebola cases in 100'000 per capita in neighboring locations. $ebolaCum - Neighb$ is the cumulative number of Ebola infections over time in neighboring locations. $ebola - Neighb \in \{0, 1\}$ is the presence of Ebola in neighboring regions (reduced form effect).

Figure B.12: Difference-in-Difference in Quarantines per cap.



Notes: The figure shows the change in conflict incidence over time due to an additional quarantine in 100'000 per capita. Regression of conflict in 1mn per capita on 6-week time dummies interacted with an ever/never quarantine dummy divided by population per 100'000. Time 0 is in July 2014, which is the first time a quarantine was ever established.

Table B.19: Margins of response

	(1) conflict(t)	(2) conflict(t)	(3) conflict(t)	(4) conflict(t)	(5) conflict(t)	(6) conflict(t)	(7) conflict(t)
ebola(t-1)	0.0146***	0.0141***				0.0148***	0.111**
	(0.0041)	(0.0039)				(0.0053)	(0.0511)
ebolaCum(t-2)		0.000464*					
		(0.0003)					
Ebola(t-1)			0.00215***	0.00213***			
			(0.0006)	(0.0006)			
EbolaCum(t-2)				0.0000561**			
				(0.0000)			
Ebola(t-1) $\in \{0, 1\}$					0.209**		
					(0.0872)		
ebola(t-1) × PostPeak						-0.000467	
						(0.0070)	
ebola(t-1) × Trend							-0.00132*
							(0.0007)
N	66574	65990	66574	65990	66574	66574	66574
R2	0.143	0.144	0.143	0.143	0.142	0.143	0.143

(Clustered SE) by Dist, Time, Chiefd, Reg × Month FE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $ebola$ are Ebola cases in 100'000 per capita, $Ebola$ are the raw number of Ebola cases, $Ebola \in \{0, 1\}$ is a dummy variable indicating whether there are Ebola cases or not in a given period. Cum refers to the cumulative. $PostPeak$ is a dummy variable indicating whether the peak of the epidemic has been reached for a given region.

Table B.20: Non-linearities?

	(1) conflict(t)	(2) conflict(t)	(3) conflict(t)	(4) conflict(t)	(5) conflict(t)	(6) conflict(t)
ebola(t-1)	0.0146***	0.0200***	0.0141***	0.0192***	0.0145***	0.0198***
	(0.0041)	(0.0061)	(0.0039)	(0.0057)	(0.0041)	(0.0058)
ebola^2(t-1)		-0.0000282**		-0.0000265*		-0.0000271**
		(0.0000)		(0.0000)		(0.0000)
ebolaCum(t-1)			0.000464*	0.000424	-0.000153	-0.000215
			(0.0003)	(0.0003)	(0.0005)	(0.0005)
ebolaCum^2(t-1)					0.000000472*	0.000000488*
					(0.0000)	(0.0000)
Observations	66574	66574	65990	65990	65990	65990
Adjusted R^2	0.109	0.109	0.109	0.110	0.109	0.110

(Clustered SE) by Dist, Time, Chiefd, Reg × Month FE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of cases over time in 100'000 per capita.

Table B.21: Countries (standardized coefficients)

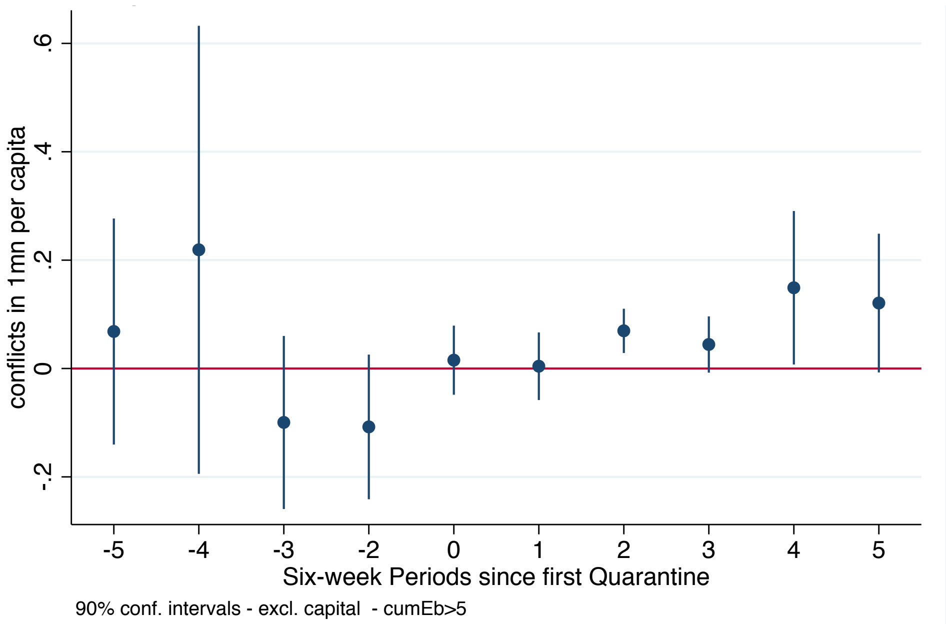
Outcome: conflict(t)	All	Liberia	Sierra Leone	Guinea
ebola(t-1)	0.0141***	0.0297***	0.0161***	0.00341
	(0.00388)	(0.00698)	(0.00478)	(0.00271)
ebolaCum(t-2)	0.000464*	-0.000782	0.000748***	0.000386
	(0.000272)	(0.000593)	(0.000106)	(0.000905)
N	65990	10396	17061	38533
Time FE	Y	Y	Y	Y
Chiefd FE	Y	Y	Y	Y
Reg × Month FE	Y	Y	Y	Y

(Clustered SE) by Dist

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of cases over time in 100'000 per capita.

Figure B.13: Event study before/after actual Quarantine - cond. on 5 Ebola cases



Notes: Change in conflict incidence after the imposition of a quarantine (population-weighted). Regression of conflict in 1mn per capita on 6-week time dummies divided by population per 100'000, only for ever quarantined locations. Time 0 is the date of the establishment of a quarantine.

Table B.22: State response Predictors: Infrastructure and Correlates of disease spread

	(1) Quarantine	(2) ETU	(3) Lab	(4) CCC	(5) None
log(ProxEpic)	0.162***	0.009	0.103**	0.009	-0.156***
	(0.043)	(0.048)	(0.046)	(0.056)	(0.051)
log(ProxEpic)^2	-0.014***	-0.001	-0.006	-0.002	0.014***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
log(Population)	-0.045	-0.118**	0.035	0.026	0.016
	(0.058)	(0.055)	(0.062)	(0.065)	(0.072)
log(Popdens)	0.039	0.179***	0.032	-0.029	-0.034
	(0.065)	(0.059)	(0.062)	(0.062)	(0.064)
Hospitals	-0.017	-0.056	0.071	0.289***	0.026
	(0.133)	(0.106)	(0.091)	(0.089)	(0.102)
Electricity	0.007	0.150	0.221	0.342**	-0.390***
	(0.206)	(0.128)	(0.210)	(0.151)	(0.144)
Water	0.124	0.197*	0.080	0.015	0.044
	(0.159)	(0.106)	(0.153)	(0.145)	(0.125)
Army	0.008	0.104	0.208	0.094	-0.136
	(0.260)	(0.103)	(0.147)	(0.172)	(0.217)
Police	-0.197	-0.193*	-0.073	-0.095	0.287
	(0.257)	(0.109)	(0.100)	(0.199)	(0.225)
Paved Roads	0.307*	0.794***	-0.203*	-0.418**	-0.012
	(0.181)	(0.083)	(0.107)	(0.159)	(0.098)
Blocked Local Roads	-2.993***	-1.165***	-0.851**	-1.663***	3.944***
	(0.473)	(0.291)	(0.341)	(0.570)	(0.305)
Mean	0.36	0.11	0.10	0.31	0.47
N	219	219	219	219	219
R2	0.52	0.28	0.22	0.27	0.43
Country FE	Y	Y	Y	Y	Y

(Clustered SE) by Dist

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All variables are pre-determined, measured before the start of the outbreak. Outcomes: military district-quarantine, Ebola treatment units (ETUs), Laboratories, Community care centers (CCCs) $\in \{0, 1\}$. $ProxEpic$ is the normalized inverse distance to the epicenter, or first index case.

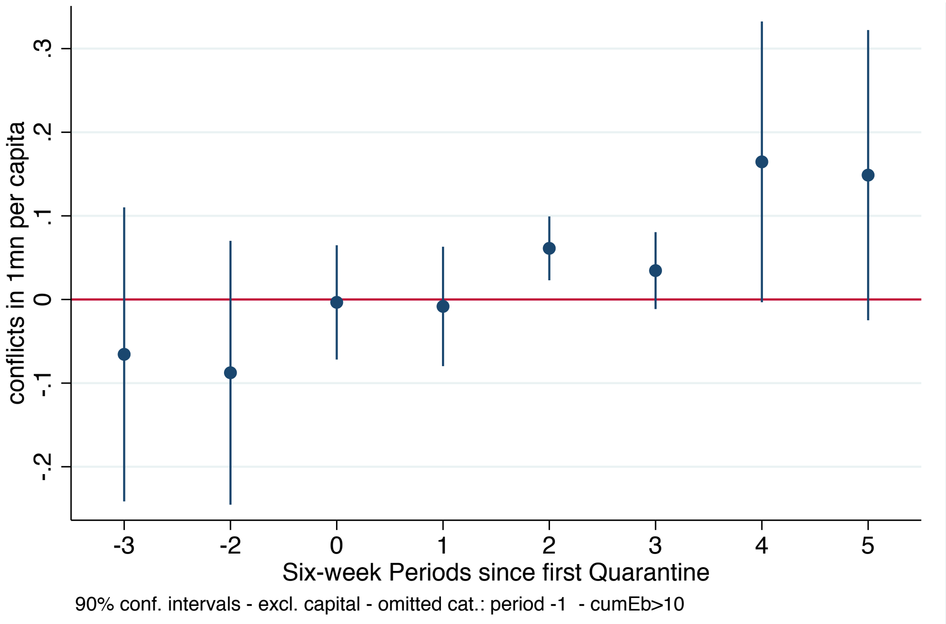
Table B.23: State response: Political motives?

	(1) Quarantine	(2) ETU	(3) Lab	(4) CCC	(5) None
Ethn Polariz.	-0.214	-0.253	-0.283	-0.158	0.031
	(0.223)	(0.218)	(0.242)	(0.264)	(0.218)
Ethn Fractionaliz.	0.532	0.744**	0.425	0.550	-0.397
	(0.334)	(0.303)	(0.327)	(0.345)	(0.271)
Ethnic Salience	0.092**	0.067**	0.047	0.008	-0.083*
	(0.040)	(0.033)	(0.036)	(0.054)	(0.046)
Strongly Relig.	0.019	0.010	0.006	-0.004	-0.006
	(0.019)	(0.023)	(0.023)	(0.030)	(0.021)
Traditional Relig.	0.002*	0.004**	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Trust People	0.001	0.011	-0.027**	-0.024*	0.009
	(0.010)	(0.012)	(0.012)	(0.014)	(0.013)
Trust President	0.319***	-0.014	0.101*	0.105	-0.155*
	(0.078)	(0.041)	(0.057)	(0.098)	(0.089)
Trust Opposition	0.208***	-0.087	0.092	0.073	-0.119
	(0.073)	(0.084)	(0.069)	(0.088)	(0.079)
Trust Local Instit.	-0.329***	0.003	-0.155**	-0.066	0.223**
	(0.083)	(0.059)	(0.062)	(0.105)	(0.092)
Trust Army	-0.178*	-0.034	0.016	0.002	0.050
	(0.104)	(0.070)	(0.071)	(0.078)	(0.091)
Trust Leaders	-0.246***	-0.131	-0.006	-0.164	0.287***
	(0.065)	(0.082)	(0.073)	(0.122)	(0.092)
Mean	0.36	0.11	0.10	0.31	0.47
N	219	219	219	219	219
R2	0.63	0.36	0.33	0.31	0.50
Country FE	Y	Y	Y	Y	Y

(Clustered SE) by Dist; cond. on Infrastructure, Epicenter proximity, Population.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

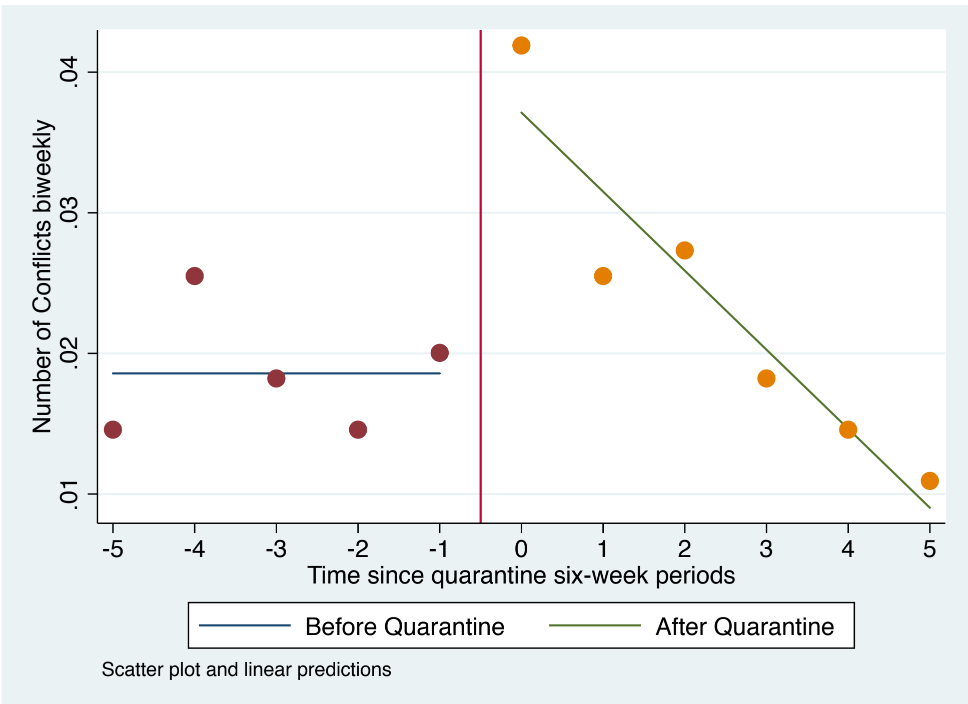
Notes: All variables are pre-determined, measured before the start of the outbreak. Outcomes: military district-quarantine, Ebola treatment units (ETUs), Laboratories, Community care centers (CCCs) $\in \{0, 1\}$.

Figure B.14: Event study before/after actual Quarantine - cond. on 10 Ebola cases



Notes: Change in conflict incidence after the imposition of a quarantine (population-weighted). Regression of conflict in 1mn per capita on 6-week time dummies divided by population per 100'000, only for ever quarantined locations. Time 0 is the date of the establishment of a quarantine.

Figure B.15: Scatter plot and linear prediction before/after Quarantine



Notes: Conflict incidence for ever-quarantined locations, before and after the Quarantine.

Table B.24: Military district-quarantines - OLS results (restricted to ever quarantined locations)

Outcome: conflict(t)	Pre-Quar		Pre/Post-Quar			
	(1)	(2)	(3)	(4)	(5)	(6)
WithinQuar			0.371*	0.446**		
			(0.1960)	(0.1918)		
PostQuar					0.436	0.550*
					(0.3054)	(0.2886)
PreQuar × Trend	-0.00560	-0.00696*				
	(0.0038)	(0.0035)				
ebola(t-1)		0.00938***		0.00897**		0.00937***
		(0.0033)		(0.0035)		(0.0033)
ebolaCum(t-2)		-0.00150**		-0.00174**		-0.00151**
		(0.0006)		(0.0007)		(0.0007)
N	1348	1233	1348	1233	1348	1233
R2	0.193	0.209	0.190	0.205	0.192	0.209
Time FE	Y	Y	Y	Y	Y	Y
Chiefd FE	Y	Y	Y	Y	Y	Y
cumEbola>20	Y	Y	Y	Y	Y	Y

(Clustered SE) by Chiefd

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. *ebola* is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of cases in 100'000 per capita. $WithinQuar$ is a dummy variable taking value 1 if the location is currently under a military quarantine and 0 otherwise. $PostQuar$ takes value 1 if the location has already been quarantined once and 0 otherwise.

Table B.25: Public Goods: Heterogeneous effects with Health Centers - cond. on cumulative Ebola

	(1) conflict(t)	(2) conflict(t)	(3) conflict(t)	(4) conflict(t)	(5) conflict(t)
ebola(t-1)	0.0221***	0.00225	0.0196**	0.0302	0.0139
	(0.0071)	(0.0039)	(0.0079)	(0.0192)	(0.0098)
ebola(t-1) × PostEmerg	-0.0200***	-0.00460	-0.0181***	-0.0317	-0.0176*
	(0.0066)	(0.0039)	(0.0066)	(0.0194)	(0.0102)
ebola(t-1) × NearETU^{end}		0.0368***			0.0375***
		(0.0052)			(0.0093)
ebola(t-1) × PostEmerg × NearETU^{end}		-0.0229***			-0.0241***
		(0.0059)			(0.0090)
ebola(t-1) × NearLab^{end}			0.0270		0.00152
			(0.0360)		(0.0369)
ebola(t-1) × PostEmerg × NearLab^{end}			-0.0184		0.00786
			(0.0377)		(0.0387)
ebola(t-1) × NearCCC^{end}				-0.0101	-0.0153
				(0.0211)	(0.0099)
ebola(t-1) × PostEmerg × NearCCC^{end}				0.0157	0.0163
				(0.0213)	(0.0102)
N	36160	33222	33222	36160	33222
R2	0.010	0.014	0.012	0.010	0.014

(Clustered SE) by Dist; Excl. capital; only Epidemic period; Time FE, Chiefd FE
Cond. on cumEbola. Omitted: ETU*PostEmerg, Lab*PostEmerg, CCC*PostEmerg
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of cases in 100'000 per capita. $PostEmerg$ is a post-treatment dummy taking value 1 after September 2014, when a great amount of emergency assistance is released. $NearETU_i^{end}$ is the normalized inverse distance to the closest Ebola treatment unit (ETU) ever available to a given location. $NearLab_i^{end}$ is the normalized inverse distance to the closest Laboratory for rapid testing of the Virus ever available to a given location. $NearCCC_i^{end}$ is the normalized inverse distance to the closest Community Care Center (CCC) ever available to a given location.

Table B.26: Public Goods: Heterogeneous effects with Health Centers - interaction with High Ebola

	(1) conflict(t)	(2) conflict(t)	(3) conflict(t)	(4) conflict(t)	(5) conflict(t)
ebola(t-1)	0.114	0.102	0.118	0.118	0.107
	(0.1146)	(0.1184)	(0.1205)	(0.1143)	(0.1175)
ebola(t-1) × PostEmerg	-0.126	-0.120	-0.131	-0.132	-0.127
	(0.1126)	(0.1168)	(0.1183)	(0.1122)	(0.1157)
ebola(t-1) × I(HighEbola)	-0.0923	-0.100	-0.0988	-0.0882	-0.0939
	(0.1144)	(0.1187)	(0.1205)	(0.1135)	(0.1169)
ebola(t-1) × PostEmerg × I(HighEbola)	0.108	0.117	0.115	0.102	0.110
	(0.1125)	(0.1171)	(0.1182)	(0.1115)	(0.1150)
ebola(t-1) × NearETU^{end}		0.0369***			0.0375***
		(0.0053)			(0.0093)
ebola(t-1) × PostEmerg × NearETU^{end}		-0.0188***			-0.0203**
		(0.0057)			(0.0091)
ebola(t-1) × NearLab^{end}			0.0272		0.00228
			(0.0360)		(0.0368)
ebola(t-1) × PostEmerg × NearLab^{end}			-0.0186		0.00635
			(0.0374)		(0.0382)
ebola(t-1) × NearCCC^{end}				-0.00986	-0.0146
				(0.0209)	(0.0095)
ebola(t-1) × PostEmerg × NearCCC^{end}				0.0180	0.0171*
				(0.0202)	(0.0095)
N	36480	33516	33516	36480	33516
R2	0.010	0.013	0.012	0.010	0.013

(Clustered SE) by Dist; Excl. capital; only Epidemic period; Time FE, Chiefd FE
Omitted: ETU*PostEmerg, Lab*PostEmerg, CCC*PostEmerg High*PostEmerg
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of cases in 100'000 per capita. $PostEmerg$ is a post-treatment dummy taking value 1 after September 2014, when a great amount of emergency assistance is released. $NearETU_i^{end}$ is the normalized inverse distance to the closest Ebola treatment unit (ETU) ever available to a given location. $NearLab_i^{end}$ is the normalized inverse distance to the closest Laboratory for rapid testing of the Virus ever available to a given location. $NearCCC_i^{end}$ is the normalized inverse distance to the closest Community Care Center (CCC) ever available to a given location.

Table B.27: Is Total Conflict predictive of the amount of Public Goods? (correlations)

	CCC		ETU		Lab	
	(1) Nr.CCCs	(2) NearCCC	(3) Nr.ETUs	(4) NearETU	(5) Nr.Labs	(6) NearLab
$\text{Confl}^{Epidemic}$	23.8*	23.8*	-1.8	-6.12	4.15	1.76
	(12.4)	(12.4)	(9.44)	(8.54)	(7.19)	(7.73)
Mean	0.31	0.11	0.11	0.09	0.10	0.08
N	572	572	572	540	572	540
R2	0.38	0.38	0.31	0.33	0.14	0.14
Region FE	Y	Y	Y	Y	Y	Y

(Clustered SE) by Dist; Controls: Ebola Total, popdens, NearEpic

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Outcomes: number or inverse distance to Ebola treatment units (ETUs), Laboratories, Community care centers (CCCs).

Table B.28: Economic mechanism?

	(1) conflict(t)	(2) conflict(t)	(3) conflict(t)	(4) conflict(t)	(5) conflict(t)
ebola(t-1)	0.0186*	0.0208***	0.0191*	0.0218***	
	(0.0102)	(0.0054)	(0.0096)	(0.0053)	
PricePalmOil(t-1)		0.0000159		0.0000153	0.00000581
		(0.0000)		(0.0000)	(0.0000)
PriceImpRice(t-1)			-0.000143*	-0.000132*	-0.000113
			(0.0001)	(0.0001)	(0.0001)
Observations	7714	7272	7309	7272	7272
R^2	0.067	0.068	0.068	0.068	0.068

(Clustered SE) by Dist, with Time FE, Chiefd FE

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita in the own region. $ebola$ is the number Ebola cases in 100'000 per capita. $ebolaCum$ is the cumulative number of Ebola infections over time. Price of palm oil and price of imported rice is are prices measured at monthly level and collected by (Glennerster et al., 2013) during the epidemic.

Table B.29: Baseline correlates of civil violence

Outcome: conflict(quarter)	Pre-Epidemic	Epidemic
	(1)	(2)
ebola Total per cap.	0.000	0.006***
	(0.000)	(0.001)
Strongly Relig	-0.280	-0.046
	(0.270)	(0.176)
Trad Relig	-0.007	0.003
	(0.012)	(0.010)
Ethnic Salience	-0.136	0.107
	(0.233)	(0.196)
Ethnic Fractionaliz.	1.586	-2.291
	(2.096)	(1.594)
Ethnic Polariz.	-1.342	1.546
	(1.695)	(1.291)
Trust Leaders	0.466	0.157
	(0.509)	(0.481)
Trust People	0.060	0.022
	(0.060)	(0.042)
Trust Local Instit.	-0.691*	-0.173
	(0.359)	(0.304)
Trust Army	-0.144	-0.360
	(0.364)	(0.358)
Mean	0.48	0.73
N	1752	1971
R2	0.03	0.05
Country FE	Y	Y
Time FE	Y	Y

(Clustered SE) by Dist; Controls: ProxEpic, ProxEpic2, Population, Population Density

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: $conflict$ are the number of conflicts in one million per capita over a quarter of a year in the pre-epidemic and in the post-epidemic period. $ebolaTotalpercap.$ is the total cumulative number of Ebola cases in 100'000 per capita measured post epidemic. The covariates are Afrobarometer data measured pre-epidemic and aggregated at our unit of observation (other variables), i.e. chiefdom, district and sub-prefecture for Sierra Leone, Liberia and Guinea, respectively. Trust in people is a summary index statistic grouping trust in neighbors, in other citizens, family members. Incumbent and opposition are summary index statistics grouping trust and votes for the either (including them separately leads to similar results).

Table B.30: Correlates of civil violence - Political preferences, War and Infrastructure

Outcome: conflict(t)	(1)	(2)	(3)	(4)
ebola(t)	0.0145**	0.0158***	0.0167***	0.0169*
	(0.0055)	(0.0057)	(0.0057)	(0.0086)
ebola(t-1) × Incumbent	-0.0000177			
	(0.0019)			
ebola(t-1) × Opposition	-0.000663			
	(0.0026)			
ebola(t-1) × Civil War		-0.145		
		(0.3363)		
ebola(t-1) × Infrastructure^{SumIndex}			0.000189	
			(0.0003)	
ebola(t-1) × Electricity				0.0383***
				(0.0129)
ebola(t-1) × Piped Water				-0.00641
				(0.0088)
ebola(t-1) × Health Centers				-0.0187
				(0.0284)
ebola(t-1) × Markets				-0.0221*
				(0.0118)
ebola(t-1) × Paved Roads				0.826***
				(0.0237)
Mean	0.0968	0.0968	0.0968	0.0968
N	23370	65208	24852	24852
R2	0.0530	0.0392	0.0503	0.0529
Time FE	Y	Y	Y	Y
Chiefd FE	Y	Y	Y	Y

(Clustered SE) by Dist; Time, Chiefd; Control: ebola × DistEpic, ebola × DistEpic^2; Excl. capital
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: t are two-week periods. $conflict$ are the number of conflicts in one million per capita. *ebola* is the number Ebola cases in 100'000 per capita. The covariates are Afrobarometer data measured pre-epidemic and aggregated at our unit of observation (other variables), i.e. chiefdom, district and sub-prefecture for Sierra Leone, Liberia and Guinea, respectively. $Infrastructure$ is a summary index statistic grouping access to roads, water, electricity, hospitals. $CivilWar$ is the sum of conflict events in each location during the wars in Liberia and Sierra Leone, starting with the first available newspaper reports from the ACLED dataset (1997-2003).

Table B.31: Correlates of civil violence - Table of p-values and q-values

	p-values and q-values				
Outcome: conflict(t)	(1)	(2)	(3)	(4)	(5)
ebola(t)	.015	.018	.001	5.18e-08	.541
ebola(t-1) × Strongly Relig.	**.059**	**.049**			**.048**
	.164	.149			.149
	.142	.132			.132
ebola(t-1) × Tradit. Relig		.235			.381
		.433			.599
		.355			.519
ebola(t-1) × Ethnic Fractional.			**.028**		.155
			.117		.342
			.101		.261
ebola(t-1) × Ethnic Polariz.			**.037**		**.004**
			.137		**.029**
			.121		**.028**
ebola(t-1) × Ethnic Salience			.364		.335
			.599		.582
			.519		.504
ebola(t-1) × Trust Leaders				**.010**	**.003**
				.050	**.029**
				.042	**.028**
ebola(t-1) × Trust Local Instit.				**.001**	.117
				.012	.277
				.011	.202
ebola(t-1) × Trust President				.408	.229
				.613	.433
				.519	.355
ebola(t-1) × Trust Opposition				.802	.559
				.828	.703
				.761	.621
ebola(t-1) × Trust Army				**.006**	.745
				.037	.828
				.033	.761
ebola(t-1) × Trust People				.784	.212
				.828	.433
				.761	.355

First row: standard p-values.
Second row: q-values introduced by Benjamini and Hochberg (1995).
Third row: sharpened two-stage q-values introduced by Benjamini, Krieger, and Yekutieli (2006).

Notes: This is a table of p-values and q-values corresponding to Table 2.10. q-values are p-values that are adjusted for the number of multiple hypoheses being tested. We adjust them considering all hypotheses tested in Tables 2.10 and B.30, following Anderson (2008).

Table B.32: Correlates of civil violence - Political preferences, War and Infrastructure - Table of p-values and q-values

	p-values and q-values			
Outcome: conflict(t)	(1)	(2)	(3)	(4)
ebola(t)	.010	.008	.004	.053
ebola(t-1) × Incumbent	.992			
	.993			
	.823			
ebola(t-1) × Opposition	.797			
	.828			
	.761			
ebola(t-1) × Civil War		.666		
		.787		
		.751		
ebola(t-1) × Infrastructure^{SumIndex}			.574	
			.703	
			.621	
ebola(t-1) × Electricity				**.004**
				.029
				.028
ebola(t-1) × Piped Water				.469
				.674
				.582
ebola(t-1) × Health Centers				.511
				.703
				.621
ebola(t-1) × Markets				**.065**
				.167
				.145
ebola(t-1) × Paved Roads				**4.16e-41**
				.001
				.001

First row: standard p-values.
Second row: q-values introduced by Benjamini and Hochberg (1995).
Third row: sharpened two-stage q-values introduced by Benjamini, Krieger, and Yekutieli (2006).

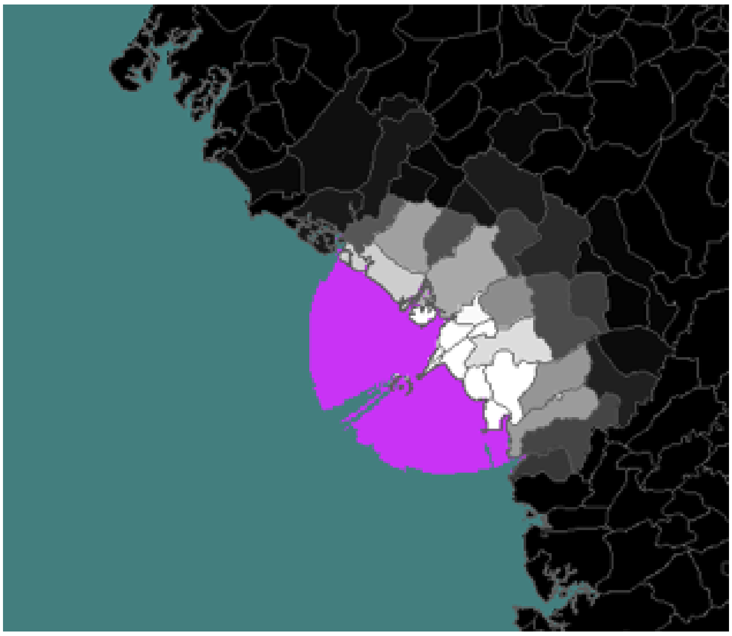
Notes: This is a table of p-values and q-values corresponding to Table B.30. q-values are p-values that are adjusted for the number of multiple hypoheses being tested. We adjust them considering all hypotheses tested in Tables 2.10 and B.30, following Anderson (2008).

C Appendix to Chapter 3

Figure C.1: Ebola radio campaigns - Summary

Ebola campaigns	Campaign	1st Starting Date	Where
Synergie Nationale	reporting	April 2014	National, Rural
Synergie Rurale	incr. inclusive	July 2014	Rural
Fondation Hirondelle	inclusive	September 2014	Rural
Synergie URTELGUI	inclusive	April, July 2014 February 2015*	Private URTELGUI
Ebola Chrono	inclusive	January 2015	National, Rural subset of Private
Spots on Ebola		February 2015*	the above

Figure C.2: Creating coverage zones by sub-prefecture

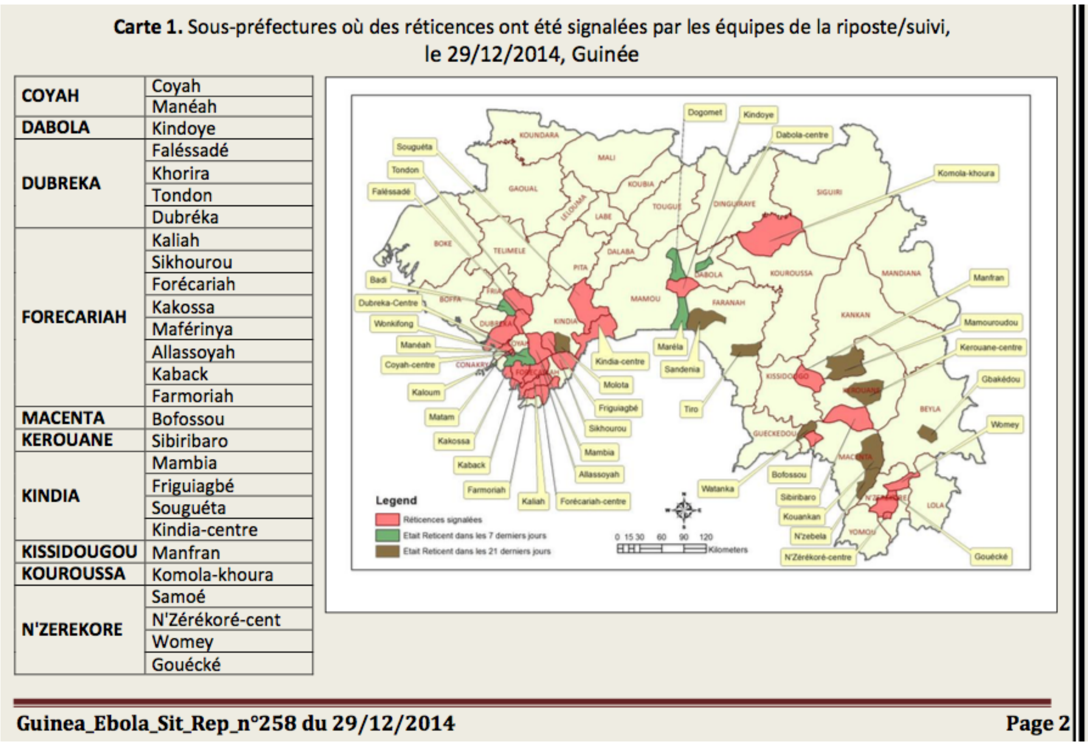


This illustrates the coverage area for one particular radio transmitter for a given signal strength. Black: 0% percent of the area is covered by that radio with at least 43 $dB\mu V/m$. Grey: lighter shades denote higher access to the radio signal. White: 100% of the area is covered with at least that signal strength.

Table C.1: Descriptives - Ebola cases

	Dataset				WHO	World Bank
Ebola cases	Confirmed	Probable	Suspect	TOTAL	Deaths	Population
Guinea	3,358	456	0	3,814	2,544	12.3 mn
Liberia	3,342	1,702	8,422	13,416	4,810	4.4 mn
Sierra Leone	8,358	0	3,545	11,903	3,956	6.3 mn
TOTAL	15,058	2,108	11,967	29,133	11,310	23 mn

Figure C.3: Scraping Resistance Data



Carte 1. Sous-préfectures où des réticences ont été signalées par les équipes de la riposte/suivi, le 29/12/2014, Guinée

COYAH	Coyah
	Manéah
DABOLA	Kindoye
DUBREKA	Faléssadé
	Khorira
	Tondon
	Dubréka
FORECARIAH	Kaliah
	Sikhourou
	Forécariah
	Kakossa
	Maférinya
	Allassoyah
	Kaback
	Farmoriah
MACENTA	Bofossou
KEROUANE	Sibiribaro
KINDIA	Mambia
	Friguiagbé
	Souguéta
	Kindia-centre
KISSIDOUGOU	Manfran
KOUROUSSA	Komola-khoura
N'ZEREKORE	Samoé
	N'Zérékoré-cent
	Womey
	Gouécké

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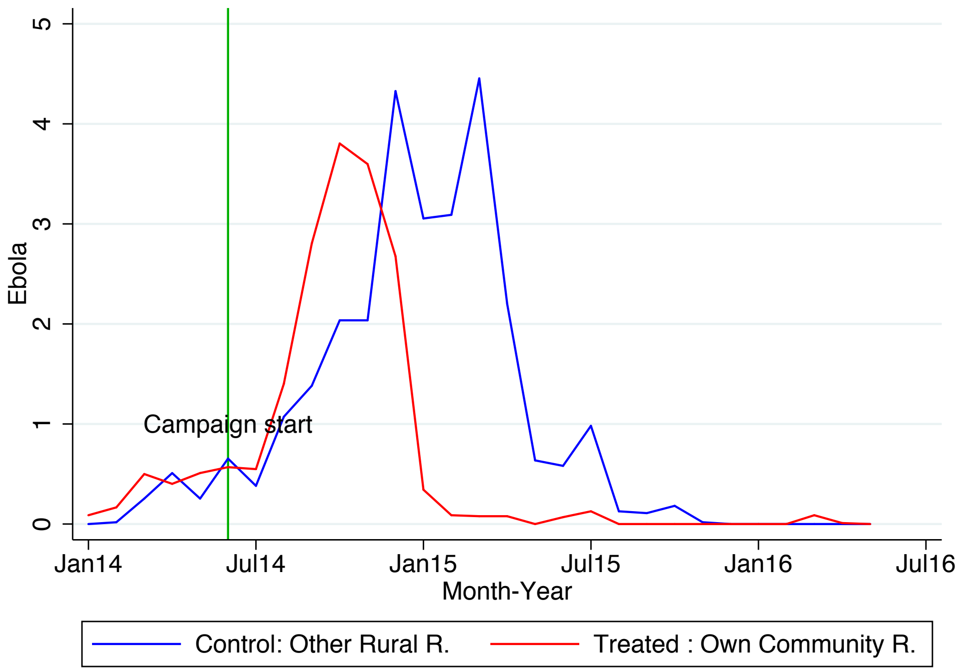
Figure C.4: Ebola in areas with above/below median access to **Own Community Rural Radio** signal

Number of Ebola cases



Log number of Ebola cases +0.01)

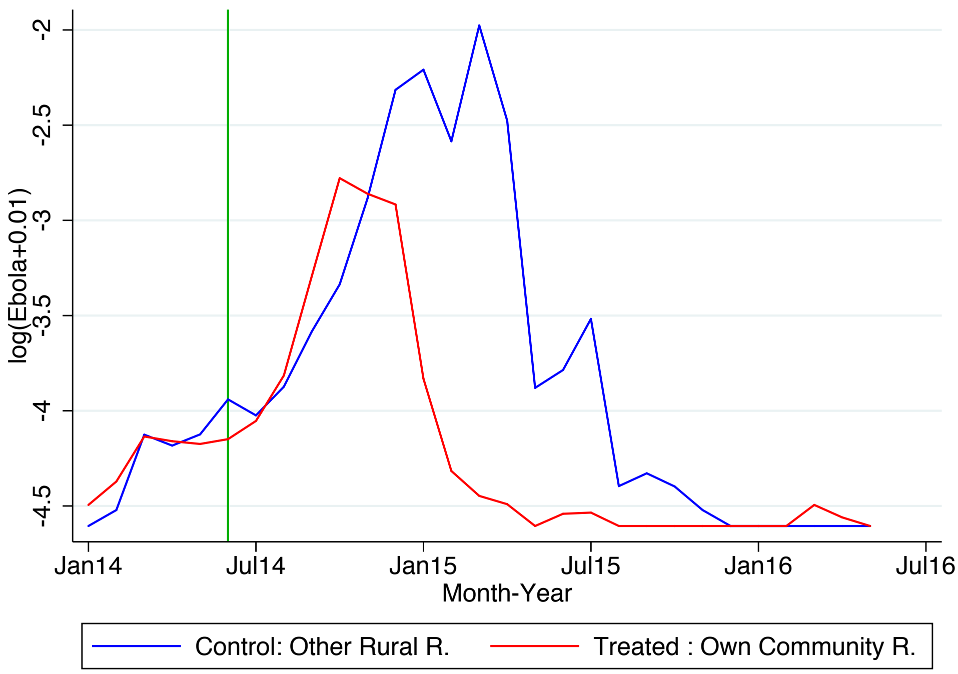


Table C.2: Event study - Outcome : log(Ebola+0, 01)

	(1)	(2)	(3)	(4)	(5)	(6)
Own Rural × (t-5)	-0.007	0.048	-0.254	-0.144	0.126	-0.275
	(0.382)	(0.385)	(0.397)	(0.379)	(0.348)	(0.426)
Own Rural × (t-4)	0.101	0.111	-0.035	-0.015	0.169	-0.061
	(0.358)	(0.389)	(0.415)	(0.369)	(0.329)	(0.444)
Own Rural × (t-3)	0.208	0.334	0.559	0.137	0.222	0.533
	(0.421)	(0.387)	(0.489)	(0.458)	(0.381)	(0.526)
Own Rural × (t-2)	0.191	0.201	0.311	0.115	0.103	0.266
	(0.328)	(0.301)	(0.390)	(0.358)	(0.293)	(0.368)
Own Rural × (t)	-0.263	-0.228	-0.302	-0.249	-0.327	-0.163
	(0.331)	(0.385)	(0.406)	(0.368)	(0.289)	(0.559)
Own Rural × (t+1)	0.150	0.126	0.319	0.071	0.089	0.100
	(0.390)	(0.398)	(0.453)	(0.474)	(0.347)	(0.546)
Own Rural × (t+2)	0.341	0.310	0.539	0.155	0.079	0.249
	(0.659)	(0.538)	(0.792)	(0.673)	(0.524)	(0.567)
Own Rural × (t+3)	0.561	0.370	1.010	0.364	0.195	0.782
	(0.942)	(0.730)	(1.061)	(0.980)	(0.705)	(0.652)
Own Rural × (t+4)	1.070	0.660	0.990	1.121	0.463	0.785
	(1.002)	(0.794)	(1.125)	(1.063)	(0.743)	(0.921)
Own Rural × (t+5)	0.286	-0.184	0.008	0.317	-0.234	-0.282
	(0.976)	(0.879)	(1.157)	(1.054)	(0.832)	(0.967)
Own Rural × (t+6)	0.266	0.151	0.435	0.135	0.235	0.279
	(0.678)	(0.754)	(0.842)	(0.659)	(0.712)	(0.890)
Own Rural × (t+7)	-1.409*	-1.185	-1.073	-1.607**	-1.113	-1.338*
	(0.760)	(0.759)	(0.890)	(0.676)	(0.721)	(0.758)
Own Rural × (t+8)	-2.054**	-1.589*	-1.974**	-2.107**	-1.659**	-1.960***
	(0.865)	(0.816)	(0.902)	(0.855)	(0.810)	(0.658)
Own Rural × (t+9)	-2.805***	-2.202**	-2.416*	-2.981***	-2.416**	-2.090**
	(0.988)	(0.906)	(1.218)	(0.977)	(0.935)	(0.861)
Own Rural × (t+10)	-2.366***	-1.860**	-1.737**	-2.558***	-1.892**	-1.629***
	(0.824)	(0.739)	(0.853)	(0.803)	(0.735)	(0.577)
N	5376	5376	5376	4352	5376	4352
Mean (no Own Rural R.)	-3.878	-3.878	-3.878	-3.878	-3.878	-3.878
R-squared	0.42	0.45	0.43	0.45	0.43	0.54
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic		Y				Y
Dist.Tower			Y			Y
Demographic				Y		Y
ETU/Lab/CCC						Y
Trust Leader					Y	

(Robust SE) clustered by Prefecture × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Event study - Outcome : Social resistance

	(1) Resistance	(2) Resistance	(3) Resistance	(4) Resistance	(5) Resistance	(6) Resistance
Own Rural × (t-5)	-0.026	-0.044	-0.022	-0.030	-0.026	0.019
	(0.083)	(0.079)	(0.102)	(0.090)	(0.088)	(0.098)
Own Rural × (t-4)	-0.007	-0.007	-0.013*	0.000	-0.006	-0.006
	(0.006)	(0.006)	(0.007)	(.)	(0.005)	(0.023)
Own Rural × (t-3)	-0.007	-0.007	-0.013*	0.000	-0.006	-0.006
	(0.006)	(0.006)	(0.007)	(.)	(0.005)	(0.023)
Own Rural × (t-2)	-0.007	-0.007	-0.013*	0.000	-0.006	-0.006
	(0.006)	(0.006)	(0.007)	(.)	(0.005)	(0.023)
Own Rural × (t)	-0.007	-0.007	-0.013*	0.000	-0.006	-0.006
	(0.006)	(0.006)	(0.007)	(.)	(0.005)	(0.023)
Own Rural × (t+1)	-0.028	-0.026	-0.037	0.000	-0.025	-0.011
	(0.024)	(0.020)	(0.027)	(.)	(0.020)	(0.026)
Own Rural × (t+2)	0.029	0.022	0.037	0.043	0.019	0.047
	(0.025)	(0.021)	(0.039)	(0.032)	(0.018)	(0.053)
Own Rural × (t+3)	-0.153	-0.211	-0.010	-0.178	-0.245	-0.049
	(0.147)	(0.144)	(0.129)	(0.187)	(0.164)	(0.146)
Own Rural × (t+4)	0.021	0.010	0.075	0.053	-0.038	0.142*
	(0.071)	(0.068)	(0.064)	(0.075)	(0.063)	(0.074)
Own Rural × (t+5)	-0.074	-0.224	-0.066	-0.064	-0.148	-0.178
	(0.297)	(0.289)	(0.308)	(0.343)	(0.312)	(0.335)
Own Rural × (t+6)	-0.050	-0.239	-0.067	-0.079	-0.029	-0.040
	(0.304)	(0.280)	(0.344)	(0.353)	(0.320)	(0.316)
Own Rural × (t+7)	-0.817**	-0.901***	-0.540*	-0.887**	-0.756**	-0.600**
	(0.310)	(0.282)	(0.295)	(0.361)	(0.302)	(0.296)
Own Rural × (t+8)	-0.418*	-0.463**	-0.231	-0.405	-0.366	-0.246
	(0.229)	(0.226)	(0.194)	(0.253)	(0.223)	(0.173)
Own Rural × (t+9)	-0.510**	-0.456**	-0.229*	-0.581***	-0.464**	-0.223
	(0.193)	(0.177)	(0.134)	(0.204)	(0.190)	(0.155)
Own Rural × (t+10)	-0.406**	-0.366**	-0.107	-0.437**	-0.328*	-0.128
	(0.181)	(0.156)	(0.159)	(0.205)	(0.174)	(0.163)
N	5376	5376	5376	4352	5376	4352
Mean (no Own Rural R.)	0.179	0.179	0.179	0.179	0.179	0.179
R-squared	0.39	0.42	0.43	0.43	0.39	0.52
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic		Y				Y
Dist.Tower			Y			Y
Demographic				Y		Y
ETU/Lab/CCC						Y
Trust Leader					Y	

(Robust SE) clustered by Prefecture × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: Event study - Outcome : % Ebola deaths in community over total Ebola deaths +1
Excluding Gueckedou (first Prefecture hit by Ebola).

	(1)	(2)	(3)	(4)	(5)	(6)
Own Rural × (t-5)	3.195	2.795	0.826	2.286	2.894	-1.792
	(2.599)	(2.462)	(2.148)	(2.532)	(2.414)	(2.370)
Own Rural × (t-4)	2.220	2.789	0.686	1.184	1.973	-1.641
	(1.988)	(2.467)	(2.141)	(1.892)	(1.820)	(2.455)
Own Rural × (t-3)	5.846**	5.250**	5.476*	5.504*	5.390**	2.473
	(2.646)	(2.616)	(2.917)	(2.825)	(2.465)	(3.245)
Own Rural × (t-2)	4.118*	4.428*	3.447	3.484	3.801*	1.455
	(2.272)	(2.565)	(2.730)	(2.333)	(2.120)	(3.052)
Own Rural × (t)	-1.592	0.679	-2.377	-1.648	-1.553	-3.998
	(2.661)	(3.692)	(3.199)	(2.851)	(2.399)	(4.573)
Own Rural × (t+1)	3.975	3.248	1.781	3.377	3.717	-1.212
	(2.806)	(2.868)	(2.958)	(3.423)	(2.625)	(4.529)
Own Rural × (t+2)	0.608	1.532	-0.614	-0.566	0.306	-3.192
	(2.241)	(2.254)	(2.754)	(2.179)	(2.029)	(2.317)
Own Rural × (t+3)	7.062	6.105	4.663	6.784	5.230	3.175
	(5.257)	(4.393)	(4.814)	(5.600)	(4.232)	(5.172)
Own Rural × (t+4)	4.936	5.273	0.888	5.399	1.965	2.777
	(5.291)	(4.400)	(4.985)	(6.010)	(4.033)	(5.385)
Own Rural × (t+5)	2.233	1.120	2.488	3.265	0.344	7.717
	(4.061)	(3.869)	(5.787)	(4.434)	(3.804)	(5.246)
Own Rural × (t+6)	0.263	-0.671	3.847	-2.343	0.572	1.243
	(4.800)	(4.291)	(4.861)	(4.434)	(4.660)	(4.698)
Own Rural × (t+7)	-5.803	-6.592	-10.118	-5.787	-6.348	-8.748
	(6.698)	(7.075)	(6.818)	(6.784)	(6.665)	(6.107)
Own Rural × (t+8)	-10.110**	-9.162*	-13.506**	-10.327**	-9.736**	-14.083***
	(4.977)	(5.018)	(5.372)	(4.865)	(4.744)	(4.645)
Own Rural × (t+9)	-11.226**	-10.689**	-8.930*	-13.166***	-10.590**	-6.393
	(4.570)	(4.160)	(5.106)	(4.854)	(4.244)	(4.872)
Own Rural × (t+10)	-8.275*	-6.557	-4.564	-9.191**	-7.587*	-0.885
	(4.269)	(4.377)	(4.464)	(4.327)	(4.019)	(4.492)
N	4768	4768	4768	3888	4768	3888
Mean (no Own Rural R.)	3.388	3.388	3.388	3.388	3.388	3.388
R-squared	0.33	0.37	0.36	0.36	0.35	0.48
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic		Y				Y
Dist.Tower			Y			Y
Demographic				Y		Y
ETU/Lab/CCC						Y
Trust Leader					Y	

(Robust SE) clustered by Prefecture × Year. Excl. Gueckedou.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: Difference-in-Differences - Dependent variable : log(Ebola+0.01)

	(1)	(2)	(3)	(4)	(5)	(6)
Own Rural × Post Rural	-0.27	-0.44	-0.27	-0.29	-0.54**	-0.37
	(0.31)	(0.26)	(0.31)	(0.31)	(0.24)	(0.32)
N	9454	9454	9454	7598	7598	7598
Mean (no Own Rural R.)	-4.33	-4.33	-4.33	-4.33	-4.33	-4.33
R-squared	0.28	0.29	0.28	0.30	0.32	0.32
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic.		Y			Y	Y
Dist.Tower			Y			Y
Demographic				Y	Y	Y
ETU/Labs/CCC					Y	Y

(Robust SE) clustered by Prefecture × Year. Excluding first Prefecture hit by Ebola.

Omitted: Other Radios × Post

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Average number of Ebola cases for the sub-sample (with no access to rural radios): 0.36. The coefficients can be interpreted as the approximate percentage change in the number of Ebola cases due to a 1 *pp* increase in access to a local radio. This is approximately $(e^{\hat{\beta}} \times 0.01 - 1) \times \frac{0.37}{0.36} \times 100\%$.

Table C.6: First Stage - Dep. Var: Heard about Ebola on the Media
Controlling for door to door campaigns

	(1)	(2)	(3)	(4)	(5)	(6)
Own Rural Radio ϕ	0.0782	0.605***	0.435***	0.418***	0.432***	0.157
	(0.0775)	(0.147)	(0.0421)	(0.107)	(0.0446)	(0.148)
Ebola Door-to-door	-0.807***	-0.804***	-0.820***	-0.819***	-0.821***	-0.830***
	(0.0329)	(0.0369)	(0.0269)	(0.0271)	(0.0276)	(0.0294)
N	2447	1234	1234	1234	1234	1234
Mean	0.71	0.68				
R-squared	0.41	0.46	0.56	0.56	0.56	0.57
F-test ϕ	1.02	17.01	106.76	15.18	93.64	1.14
Controls			Y	Y	Y	Y
Distance to Transmitter ϕ				Y		Y
Distance to Rural Radio Transmitter					Y	Y
Other Radio Signals						Y
Cond. Rural Radio > median		Y	Y	Y	Y	Y

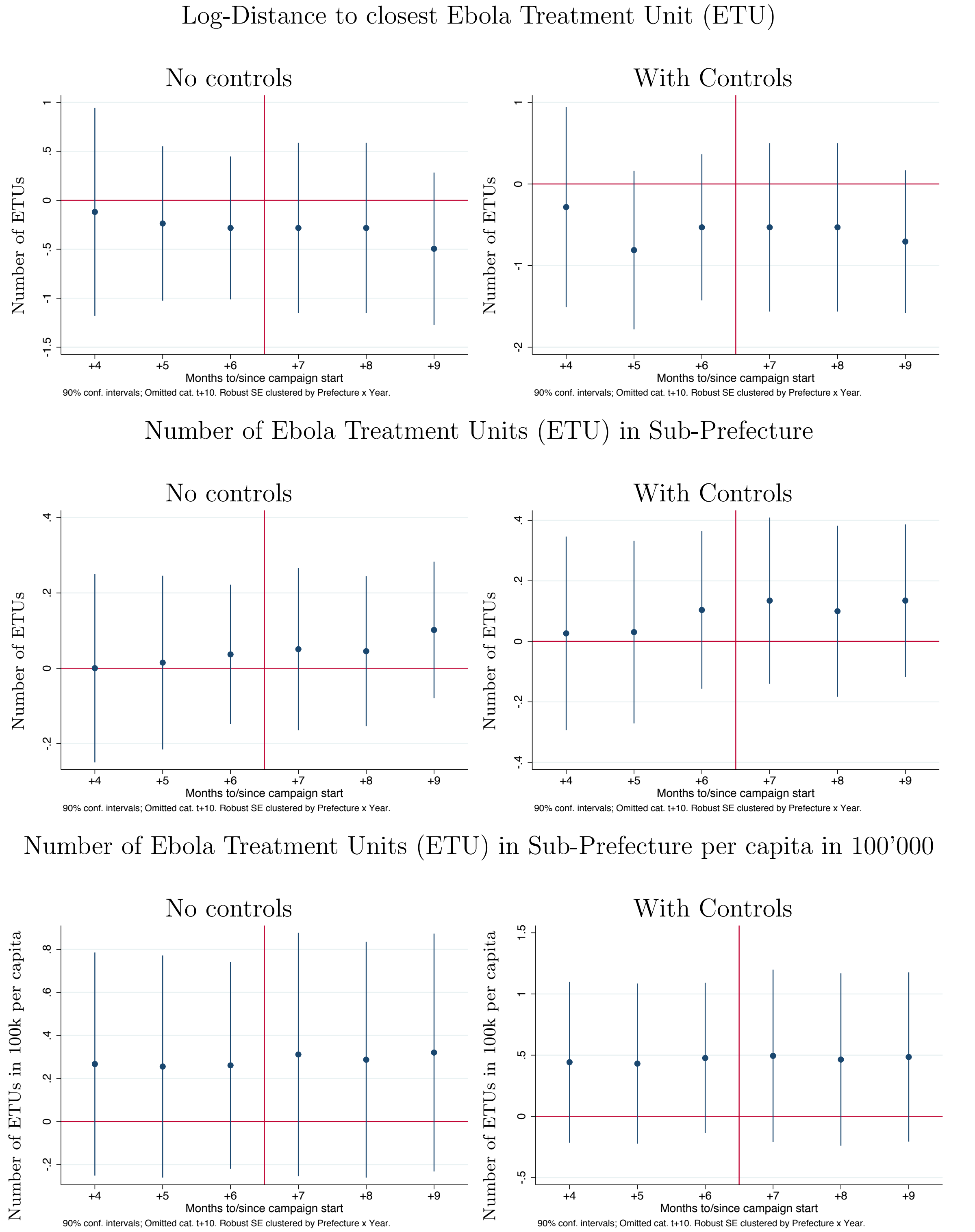
(Robust SE) clustered by Sub-prefecture. With Region FE.

Controls: pop, dist. epic., wealth, educ, gender, elect, water, health fac., urban

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS).

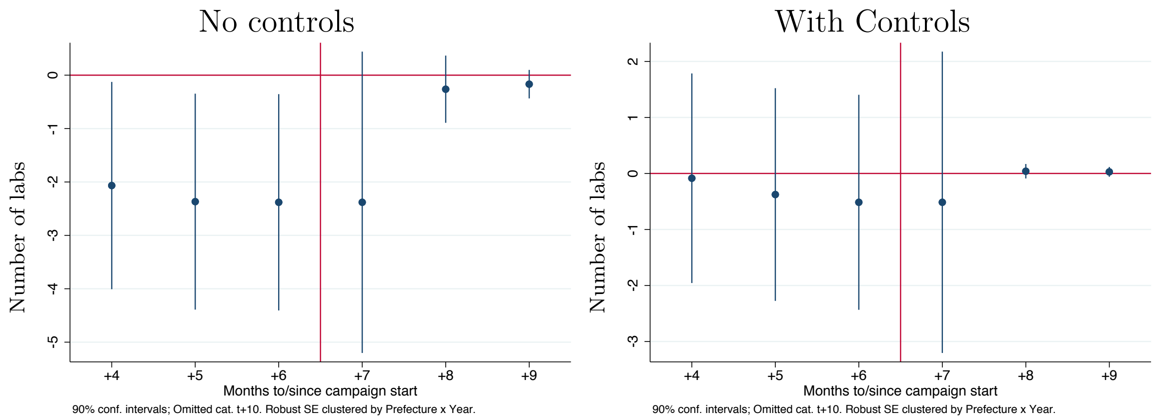
Figure C.5: Event studies - Placebo exercise
Pre/Post Rural campaign by access to Own Community Rural Radio



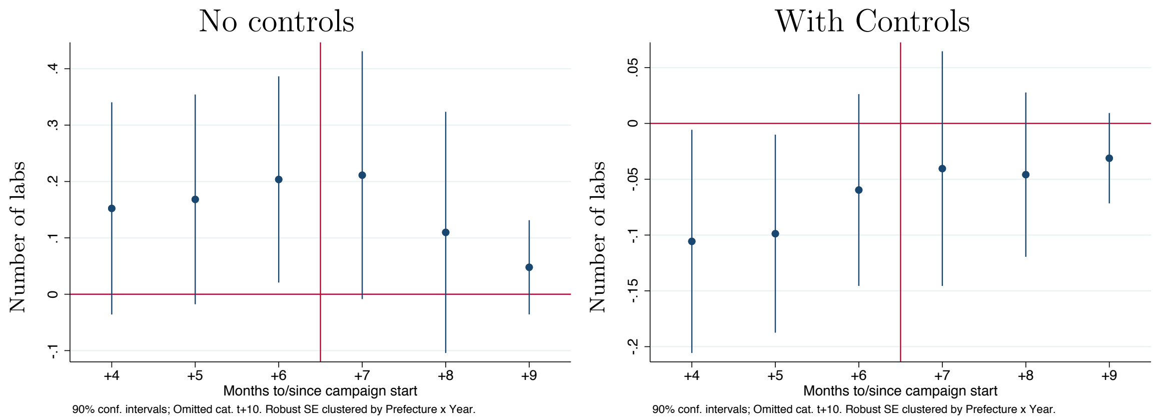
Notes: 90% confidence intervals. Robust Standard Errors clustered by Prefecture × Year. Controls: wealth level, education, rural, population, population^2, population-density; log-distance to epicenter, to the closest radio transmitter from any radio, national, private, rural, own rural radio (working and pre-existing) × time-dummies.

Figure C.6: Event studies - Placebo exercise
Pre/Post Rural campaign by access to Own Community Rural Radio

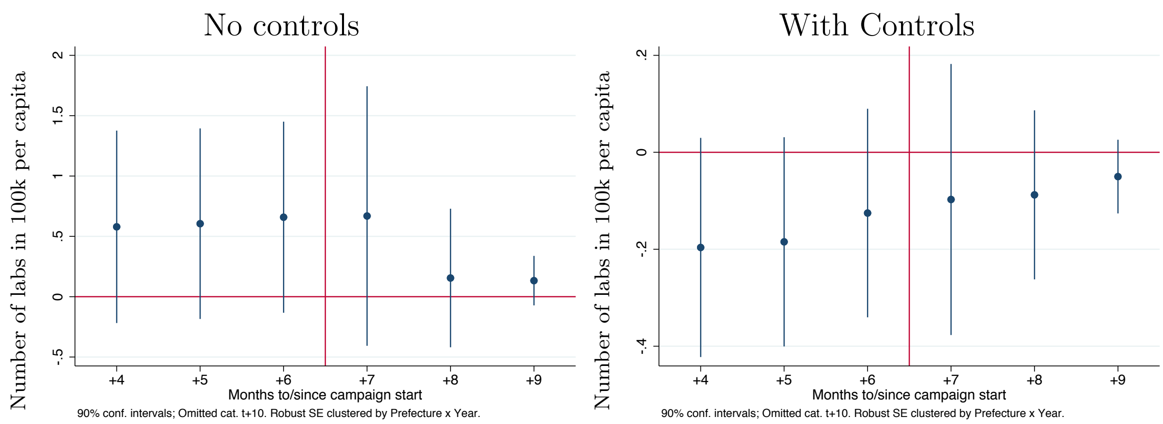
Log-Distance to closest Laboratory



Number of Laboratories in Sub-Prefecture



Number of Laboratories in Sub-Prefecture per capita in 100'000



Notes: 90% confidence intervals. Robust Standard Errors clustered by Prefecture × Year. Controls: wealth level, education, rural, population, population^2, population-density; log-distance to epicenter, to the closest radio transmitter from any radio, national, private, rural, own rural radio (working and pre-existing) × time-dummies.

Table C.7: Having heard about Ebola on the Media (1)
Conditional on above median access to any rural radio.

	Ebola Knowledge				Ebola exists			
	(1) OLS	(2) OLS	(3) Reduced F.	(4) 2SLS	(5) OLS	(6) OLS	(7) Reduced F.	(8) 2SLS
Ebola Any Info	0.251^{**}				0.0722^{**}			
	(0.109)				(0.0339)			
Ebola Info on Radio/TV	0.00364	0.190^{***}		-0.310	-0.0103	0.0406^{*}		-0.0716
	(0.0248)	(0.0592)		(0.262)	(0.00854)	(0.0203)		(0.0659)
Own Rural			-0.130				-0.0299	
			(0.111)				(0.0273)	
Ebola Door-to-door		0.204^{***}	0.0525^{**}	-0.202		0.0533^{***}	0.0210^{***}	-0.0376
		(0.0626)	(0.0229)	(0.206)		(0.0191)	(0.00673)	(0.0534)
N	1234	1234	1234	1234	1234	1234	1234	1234
Mean	2.93				0.98			
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Distance Transmitter	Y	Y	Y	Y	Y	Y	Y	Y
> median Rural R.	Y	Y	Y	Y	Y	Y	Y	Y

(Robust SE) clustered by Sub-prefecture. With Region FE. Conditional on above median access to any Rural radio
Controls: pop, dist. epic., wealth, educ, gender, elect, water, health fac., urban
Instrument: Mean access to a Rural Radio from Own Community.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS).

Table C.8: Having heard about Ebola on the Media (2)
Conditional on above median access to any rural radio.

	Fear of Treatment				Neighbours seek more Treatment			
	(1) OLS	(2) OLS	(3) Reduced F.	(4) 2SLS	(5) OLS	(6) OLS	(7) Reduced F.	(8) 2SLS
Ebola Any Info	-0.175^{***}				-0.0203			
	(0.0644)				(0.0860)			
Ebola Info on Radio/TV	0.0124	-0.0953^{**}		-0.629^{**}	0.139^{***}	0.149^{**}		0.332
	(0.0163)	(0.0434)		(0.276)	(0.0327)	(0.0583)		(0.347)
Own Rural			-0.280^{*}				0.139	
			(0.147)				(0.127)	
Ebola Door-to-door		-0.0994^{*}	-0.0161	-0.532^{**}		0.0323	-0.0917^{**}	0.181
		(0.0524)	(0.0195)	(0.233)		(0.0644)	(0.0355)	(0.293)
N	1232	1232	1232	1232	1234	1234	1234	1234
Mean	0.07				0.28			
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Distance Transmitter	Y	Y	Y	Y	Y	Y	Y	Y
> median Rural R.	Y	Y	Y	Y	Y	Y	Y	Y

(Robust SE) clustered by Sub-prefecture. With Region FE. Conditional on above median access to any Rural radio
Controls: pop, dist. epic., wealth, educ, gender, elect, water, health fac., urban
Instrument: Mean access to a Rural Radio from Own Community.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS).

Table C.9: Having heard about Ebola on the Media (3)
Conditional on above median access to any rural radio.

	Chlorine Use						
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Reduced F.	(6) Reduced F.	(7) 2SLS
Ebola Any Info	0.00942		0.185				
	(0.0212)		(0.119)				
Ebola Info on Radio/TV	-0.00552	-0.00148	-0.00468			-0.0628	0.0803
	(0.00768)	(0.0105)	(0.00756)			(0.0824)	(0.213)
Own Rural				-0.0262	-0.0146		
				(0.0352)	(0.0360)		
Ebola Door-to-door		0.00189		0.00364		-0.0478	
		(0.0137)		(0.00888)		(0.0689)	
Info from Family			0.188		0.00913		0.0714
			(0.121)		(0.0190)		(0.161)
Knows Ebola Victim			0.0194*		0.0191*		0.0203*
			(0.0107)		(0.0111)		(0.0111)
N	1234	1234	1234	1234	1234	1234	1234
Mean	0.97						
Controls	Y	Y	Y	Y	Y	Y	Y
Distance Transmitter	Y	Y	Y	Y	Y	Y	Y
> Median Rural R.	Y	Y	Y	Y	Y	Y	Y

(Robust SE) clustered by Sub-prefecture. With Region FE.
Controls: pop, dist. epic., wealth, educ, gender, elect, water, health fac., urban
Conditional on above median access to any Rural radio
Instrument: Mean access to a Rural Radio from Own Community.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS).

Table C.10: Refused Burials over time for each prefecture

Outcome: Refused burials in 100'000 per capita

	(1) t	(2) t+1	(3) t+2	(4) t+3
Red Cross Radio	-0.041	-0.326***	-0.166	-0.918**
	(0.067)	(0.108)	(0.185)	(0.418)
Red Cross Radio × Social Mobilis. Preventive	-0.053	-0.010	0.021	0.177**
	(0.041)	(0.034)	(0.034)	(0.085)
Social Mobilis. Preventive	0.189**	0.227***	0.034	-0.074
	(0.092)	(0.085)	(0.070)	(0.059)
Social Mobilis. Response	-0.088	-0.270*	-0.342*	-0.354
	(0.145)	(0.162)	(0.203)	(0.288)
N	238	204	170	136
Mean	0.12	0.11	0.10	0.10
R-squared	0.73	0.86	0.92	0.96
Radio Emis.(t-1, t-2)	Y	Y	Y	Y
Soc.Mob.Rep.(t-1, t-2)	Y	Y	Y	Y
Soc.Mob.Prev.(t-1, t-2)	Y	Y	Y	Y
Red Cross activity	Y	Y	Y	Y
Pop/Dens/Dist Epic × Trend	Y	Y	Y	Y

Robust Standard Errors in parentheses clustered by Prefecture × Semester

Controlling for Pref. FE, Time FE.

Red Cross activity: surveillance, transport, cholera kits

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: International Federation of the Red Cross in Guinea, April-December, 2015

The outcome variable is *refused burials* in 100'000 per capita, with mean (std. dev.) 0.11 (0.39). *Red Cross Radio* are the number of radio emissions aired and here we standardized the original variable which had mean (std. dev.) 0.85 (3.29). *Social Mobilis. Preventive* and *Social Mobilis. Response* are a standardized variable measuring the number of volunteers conducting door-to-door campaigns either for prevention or as a response to resistance behavior. The original variables had mean (std. dev.) 548 (1786) and 2793 (6729), respectively.

Supplementary Appendices

D Supplementary Appendix to Chapter 2

Table D.1: Conflict events reported in Newspapers (1)

Ebola-related violence during the Ebola outbreak in Western Africa

- "At least 21 members of a government outreach team were injured when residents of Wome near Nzerekore attacked them with sticks and stones, thinking they were coming to bring Ebola to the village. 8 of them were killed." 8 reported fatalities, Womey, Guinea, *Agence France Presse*, September 2017.
- "An ambulance carrying suspected Ebola patients crashed into a ditch in the northwestern district of Port Loko after a mob pelted it with stones. No injuries reported." *Port Loko, Sierra Leone, Oct 2014, Agence France Presse*
- "Hundreds of youth violently prevented the installation of an Ebola treatment center, setting fires and breaking furniture." Kissidougou, Guinea, *Agence France Presse*, Dec 2014
- "Residents attacked a group of three police officers and their driver who stopped on their way to a funeral, claiming the victims were spreading Ebola and had killed a local resident whom one of the victims had given a sedative. The mob used machetes." Kindia, Guinea, *Agence France Presse*, Jan 2015
- "Thousands of protesters marched on the main Ebola hospital in Kenema and threatened to burn it down and remove the patients after a rumour spread about "cannabalistic rituals" occurring there; police fired tear gas to disperse the crowd." Kenema, Sierra Leone, *Reuters*, July 2014
- "Heavy rioting took place in the West Point neighbourhood between residents and police in response to the imposition of a curfew and quarantine." Montserrado, Liberia, *FrontPageAfrica* August 2014
- "Protesters barricaded one of the main entrances of the ELWA hospital to protest against the establishment of an Ebola Center in the hospitals compound." Montserrado, Liberia, *The Inquirer*, July 2014
- "An angry crowd confronted Red Cross workers regarding the burial of an Ebola victim. The police tried unsuccessfully to calm the situation as the rioters burned a Red Cross vehicle.", Conakry, Guinea, *Xinhua News*, December 2014

Table D.2: Conflict events reported in Newspapers (2)

Non-Ebola-related violence during the Ebola outbreak in Western Africa

- "Security forces in Labe killed a protester and wounded four others, witnesses said Thursday, as opposition supporters clashed with police at anti-government rallies in its largest towns and cities." 1 reported fatality, Labe, Guinea, *Agence France Presse*, April 2015
- "Twenty people were arrested and two police officers injured during a riot at the Plam Oil Production project in Mattru Jong, after stakeholders incited people against a government takeover of the project." Bonthe, Sierra Leone, *Concord Times* May 2014
- "A motorcyclist was killed by a soldier of the Armed Forces of Liberia following a scuffle on Tuesday in Thinker Village Community in Paynesville. Meanwhile, police have arrested the soldier and are investigating the event." 1 reported fatality. Montserrado, Liberia, *Front Page Africa*, April 2015
- "An unknown number of people are feared injured or dead following alleged clashes between members of the traditional Poro or Sande Societies in Grand Bassa County, mainly in Kpokon. Several houses were burnt down in the clashes." 10 fatalities reported." Grand Bassa, Liberia, *Front Page Africa*, April 2016

Table D.3: Conflict events reported in Newspapers (3)

Civil violence in other epidemic outbreaks throughout Africa

- "A man was shot dead and several others injured on Wednesday in fresh rioting in northern Haiti, as protesters clashed with UN peacekeepers blamed for the cholera outbreak, a police source said. ", Port-au-Prince, *The Telegraph*, November 2010.
- "In Toamasina, it is reported that health workers and volunteers working in the fight against the plague epidemic have been hunted by furious residents. The people used sticks and knives to frighten the health workers.", Tomasina, Madagascar, *Outbreak News Today, L'Express de Madagascar*, October 2017.
- "Cholera treatment centre attacked due to misinformation and suspicion among locals that it was spreading the disease", Ancuabe, Mozambique, *All Africa*, 2009.
- "A Frelimo branch secretary was seized by an angry mob and killed, over accusations that party leaders were spreading cholera", Maputo, Mozambique, *Agencia de Informacao de Mocambique*, 2013.
- "A Frelimo official and community leader in Mecufi, was buried alive, up to his neck, and then killed by an angry mob over accusations that party leaders were spreading cholera in Macomia district", *Agencia de Informacao de Mocambique*, 2013.
- "Dodoth warriors kill UPDF soldier who had been suffering from malaria", Kalapata, Uganda, *All Africa*, 2009.
- "Two men where allegedly killed by their sons after the sons accused their fathers of being 'witches', following the deaths of a sister and brother due to childbirth and malaria respectively", Buba, DRC, *Radio Okapi*, 2016.
- "500 AIDS activists marched by a police station to protest police brutality", Johannesburg, South Africa, *Reuters News*, 2003.

Table D.4: Newspapers pre and post Epidemic - Guinea

Newspapers reporting on conflict in Guinea	Number of Articles		
	pre-Ebola	post-Ebola	Total
Agence France Presse	29	35	64
Aminata	24	23	47
Associated Press	12	6	18
Guineenews	3	7	10
Media Foundation for West Africa	2	1	3
Radio France Internationale	11	4	15
Reuters	2	1	3
Xinhua	10	17	27
Africa News	1	0	1
Afrik.com	12	0	12
AfriquInfos	1	0	1
All Africa	5	0	5
AngolaPress	9	0	9
Committee to Protect Journalists	1	0	1
Daily Record	1	0	1
Guinee 7	2	0	2
Human Rights Watch (Washington, DC)	1	0	1
IHS Global Insight Daily Analysis	1	0	1
Jeune Afrique	4	0	4
Kankan Radio	1	0	1
Le Point	2	0	2
Lejourguinee.com	3	0	3
Relief Web	2	0	2
Reuters Africa	1	0	1
Slate Afrique	1	0	1
Sunday Mail	1	0	1
Xinau General News	3	0	3
Mali Actu	1	0	1
AlertNet (London)	0	1	1
Amnesty International	0	1	1
Daily Independent (Lagos)	0	1	1
Deutsche Welle	0	2	2
France 24	0	2	2
International Freedom of Expression Exchange Clearing House	0	1	1
PBS News Hour	0	1	1
Syndigate Media	0	1	1
Video News	0	1	1
Voice of America (Washington, DC)	0	1	1
Total	146	106	252

Table D.5: Newspapers pre and post Epidemic - Sierra Leone

Newspapers reporting on conflict in Sierra Leone	Number of Articles		
	pre-Ebola	post-Ebola	Total
Associated Press International	1	1	2
Awareness Times	5	2	7
Concord Times	6	14	20
APANEWS	1	0	1
Agence de Presse Africaine	1	0	1
Cocoricko	2	0	2
Public Agenda	1	0	1
Think Africa Press	2	0	2
Agence France Presse	0	6	6
Al Jazeera - English	0	1	1
Aminata	0	1	1
Awoko.org	0	12	12
BBC News	0	1	1
CBC News	0	1	1
Media Foundation for West Africa	0	2	2
Pan African News Agency	0	4	4
Reuters	0	4	4
Star Africa	0	1	1
The Mercury (South Africa)	0	1	1
Vice News	0	1	1
Voice of America (Washington, DC)	0	1	1
Total	19	53	72

Table D.6: Newspapers pre and post Epidemic - Liberia

Newspapers reporting on conflict in Liberia	Number of Articles		
	pre-Ebola	post-Ebola	Total
Agence France Presse	4	5	9
Associated Press	1	2	3
Front Page Africa	6	2	8
Heritage	5	18	23
New Dawn Liberia	5	1	6
New Democrat	14	1	15
The Analyst	7	2	9
The Inquirer	4	21	25
The NEWS	6	13	19
The New Dawn	15	55	70
The New Republic Liberia	5	14	19
All Africa	2	0	2
Liberian News	2	0	2
Liberian Times	3	0	3
Reuters	1	0	1
The Front Page Africa	1	0	1
The Informer	4	0	4
The Liberian Times	4	0	4
The New Zealand Herald	2	0	2
Voice of America	1	0	1
Associated Press International	0	1	1
Daily Observer	0	1	1
Foreign Policy	0	1	1
FrontPageAfrica	0	49	49
GNN Liberia	0	1	1
International Business Times	0	2	2
International Freedom of Expression Exchange Clearing House	0	2	2
Leadership (Abuja)	0	1	1
Liberia News Agency	0	6	6
Liberian Observer	0	18	18
PBS News Hour	0	1	1
Radio France Internationale	0	2	2
Reporters Sans Frontieres (RSF)	0	1	1
Syndigate Media	0	4	4
The Mercury (South Africa)	0	1	1
Total	92	225	317

Figure D.1: Raw data - Weekly Ebola cases and Conflict incidence for each prefecture in Guinea (1)

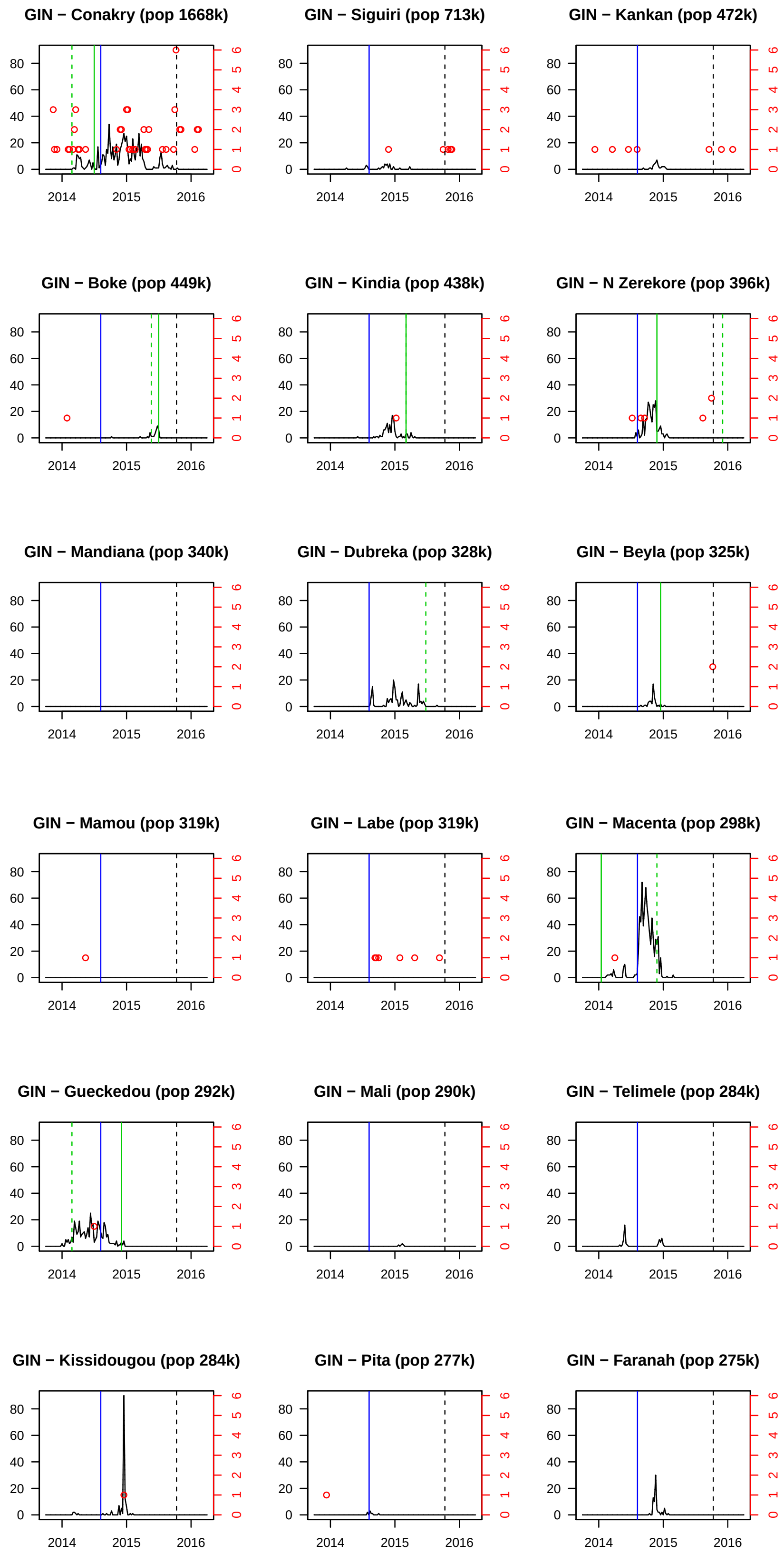


Figure D.2: Raw data - Weekly Ebola cases and Conflict incidence for each prefecture in Guinea (2)

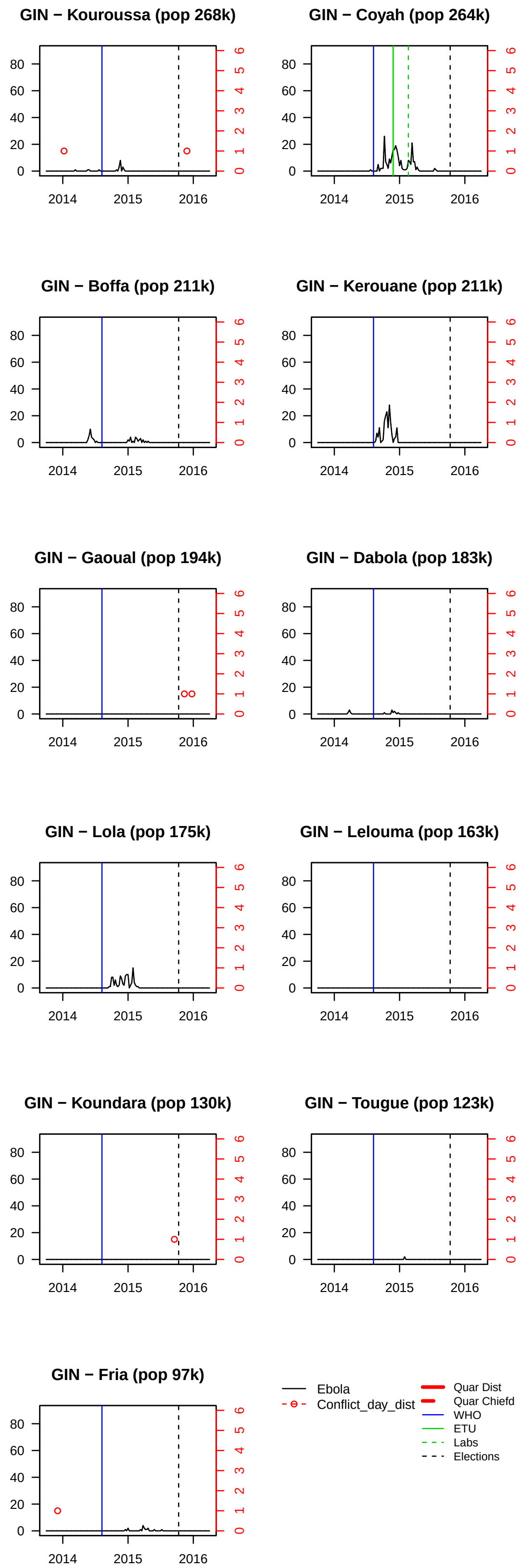


Figure D.3: Raw data - Weekly Ebola cases and Conflict incidence for each county in Liberia

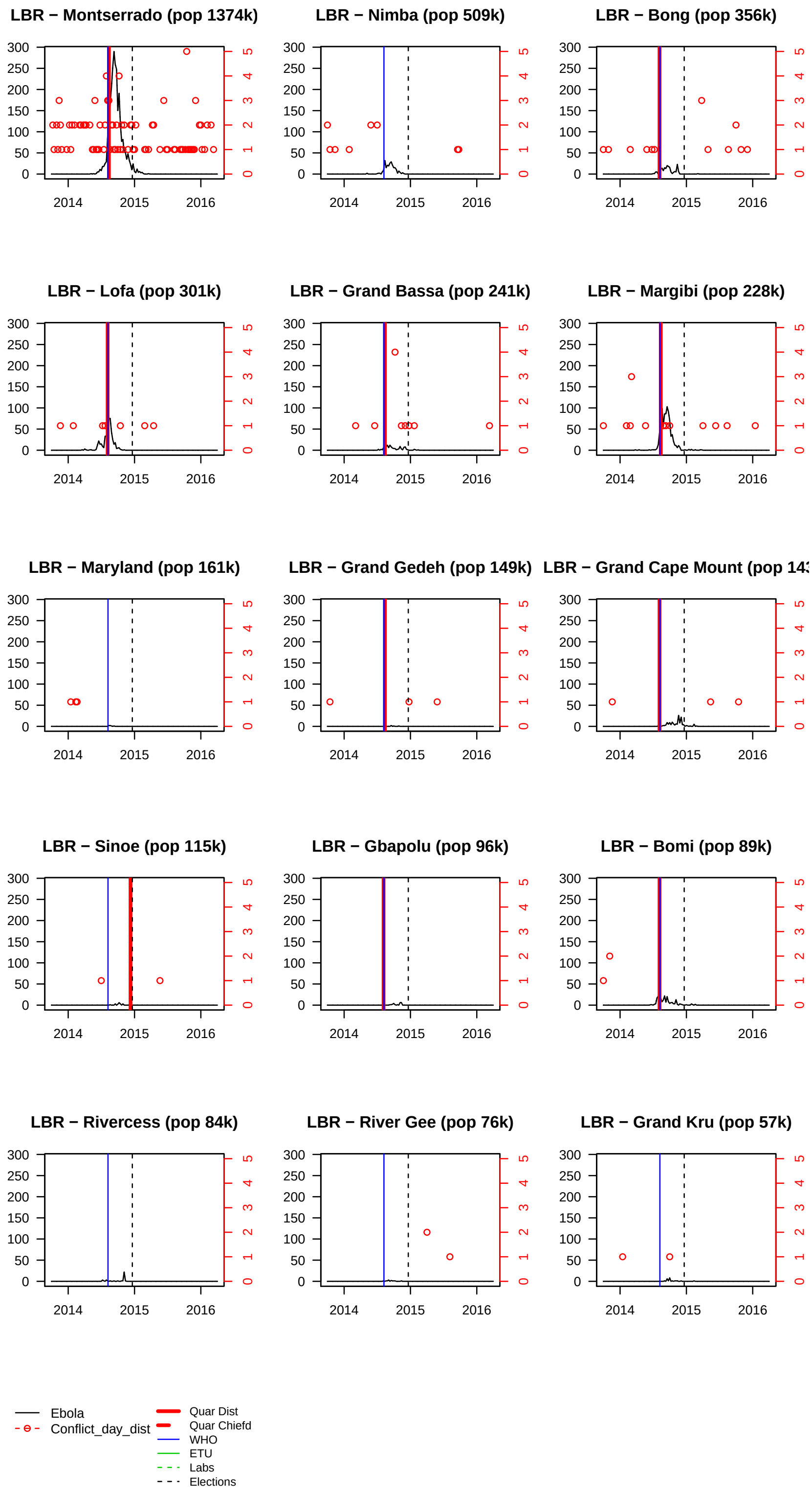
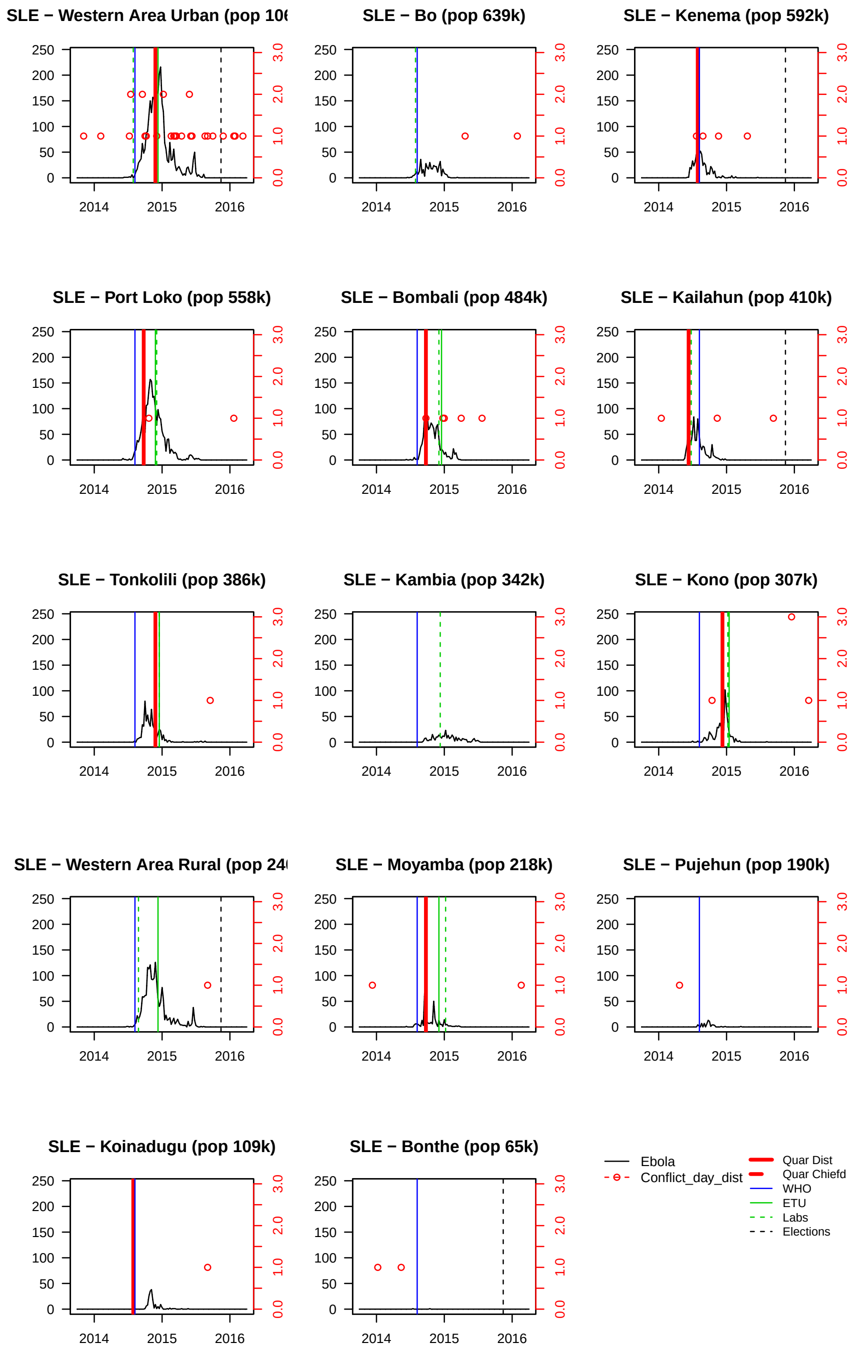


Figure D.4: Raw data - Weekly Ebola cases and Conflict incidence for each district in Sierra Leone



E Supplementary Appendix to Chapter 3

Figure E.1: Ebola program schedules for two Rural Radios

Ebola program on Gaoual Rural Radio

Program	Schedule	Length
Micro-programs	7.40pm	3min
Round Tables	9pm	30min
Magazines	9.40pm	15min
Interviews	10.05pm	20min
Reporting	9.10pm	22min
Interactive	9.00pm	60min
Sensitivization	9.05pm	45min
Days: Monday-Friday		

Ebola program on Gueckedou Rural Radio

Program	Length
Micro-programs	2-5min
Round Tables	25-30min
Magazines	15-20min
Interactive	50-60min
Spots	1-2min
Schedule: Monday-Sunday; 8-10am and 18-23am	

Table E.1: Summary Statistics - Outcomes by median access to Own Rural Radio

	Mean (Std. Dev.)			Mean (Std. Dev.)		
	Low Local R.	High Local R.	Total	Low L.R.	High L.R.	Total
Ebola cases	0.912	0.557	0.678			
	(3.786)	(4.457)	(4.243)			
Ebola cases per capita in 100k	2.083	1.893	1.958			
	(11.20)	(16.16)	(14.65)			
Log Ebola+0,01	-3.887	-4.239	-4.119			
	(2.003)	(1.462)	(1.675)			
Log Ebola+1	0.211	0.104	0.140			
	(0.649)	(0.475)	(0.543)			
Log Ebola cases in 100k per cap. +1	0.251	0.159	0.190			
	(0.807)	(0.694)	(0.736)			
Resistance behavior	0.186	0.0820	0.117			
	(0.695)	(0.424)	(0.534)			
Ebola total deaths	0.549	0.393	0.446			
	(2.274)	(3.194)	(2.914)			
Ebola deaths in community	0.250	0.152	0.185			
	(1.115)	(1.427)	(1.330)			
Ebola deaths in ETU	0.299	0.241	0.261			
	(1.353)	(2.049)	(1.841)			
Community over ETU deaths ×100	3.720	1.618	2.335			
	(13.33)	(9.046)	(10.75)			
Refused burials				0.192	0.131	0.160
				(0.819)	(0.787)	(0.802)
Refused burials in 100k per cap.				0.0877	0.0310	0.0579
				(0.374)	(0.184)	(0.291)
Observations	5017			551		

1st block: Sub-prefecture × Month (January 2014 - May 2016). 2nd: Prefecture × Month (April-December 2015).
Low Local R. (High Local R.): below (above) median access to Own Rural Radio.
For 173 Sub-Pref with above median access to any Rural Radio.

Notes: These are means by access to local radios, conditional on access to rural radios, are shown in Table E.1. To see descriptives on the full sample studied see Table 3.4. For aggregate statistics on Ebola see Table C.1.

Table E.2: Summary Statistics
Total Outcomes by date & median access to Own Rural Radio

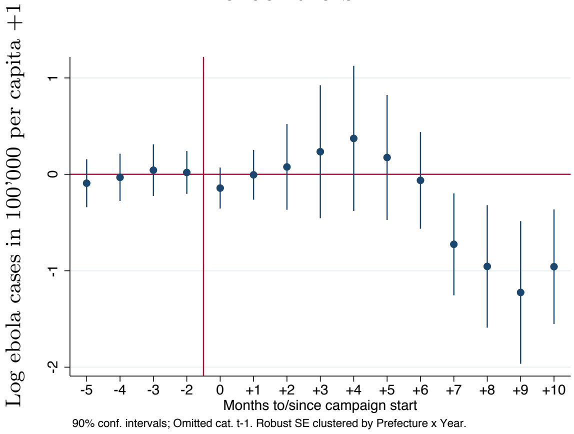
	Sum (Count)			Sum (Count)			Sum (Count)		
	Low R.	High R.	Total	Low R.	High R.	Total	Low R.	High R.	Total
Ebola cases	1560	1842	3402	1446	1558	3004	849	90	939
	(1711)	(3306)	(5017)	(1298)	(2508)	(3806)	(1003)	(1938)	(2941)
Ebola cases per capita in 100k	3563.6	6259.5	9823.1	3391.7	5259.0	8650.7	2303.5	239.2	2542.8
	(1711)	(3306)	(5017)	(1298)	(2508)	(3806)	(1003)	(1938)	(2941)
Observations	5017			3806			2941		
Cond. period Post				7/2014			12/2015		

Sub-prefecture (January 2014 - May 2016)
Low R. (High R.): below (above) median access to Own Rural Radio.
For 173 Sub-Pref with above median access to any Rural Radio. After July 2014

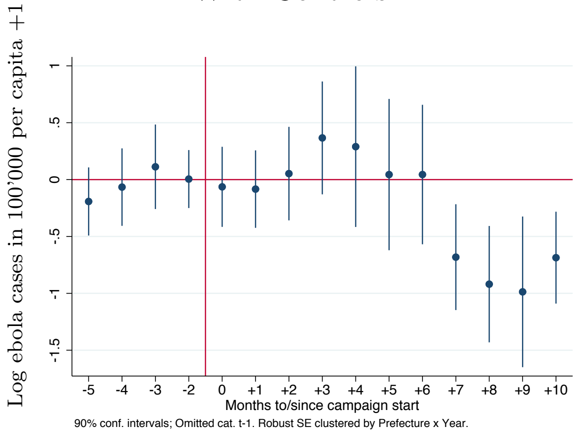
Figure E.2: Event studies - Pre/Post Rural campaign by access to Own Community Rural Radio

Log ebola cases in 100'000 per capita +1

No controls

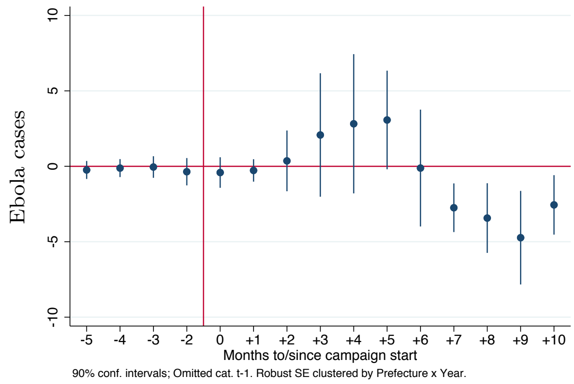


With Controls

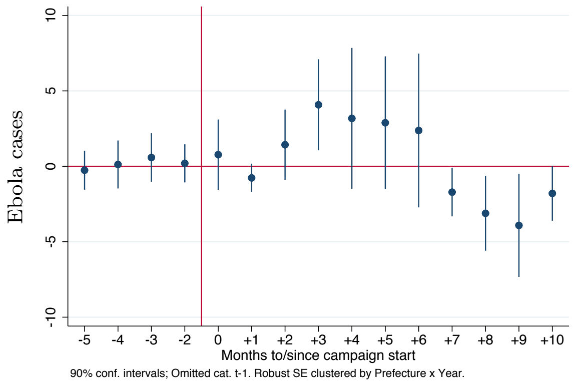


Ebola cases

No controls

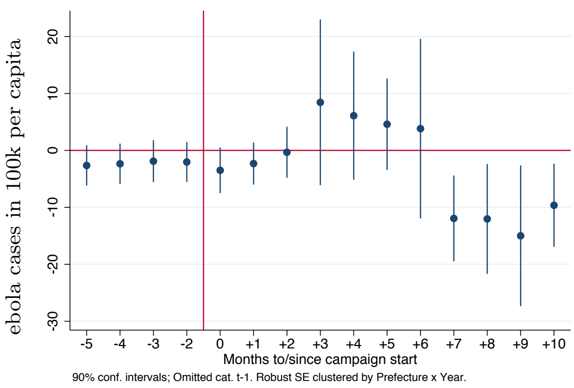


With Controls

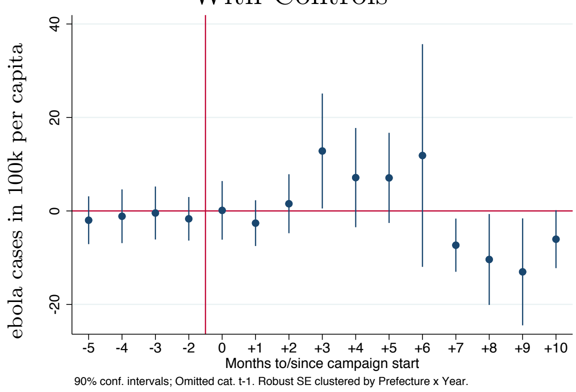


ebola cases in 100'000 per capita

No controls



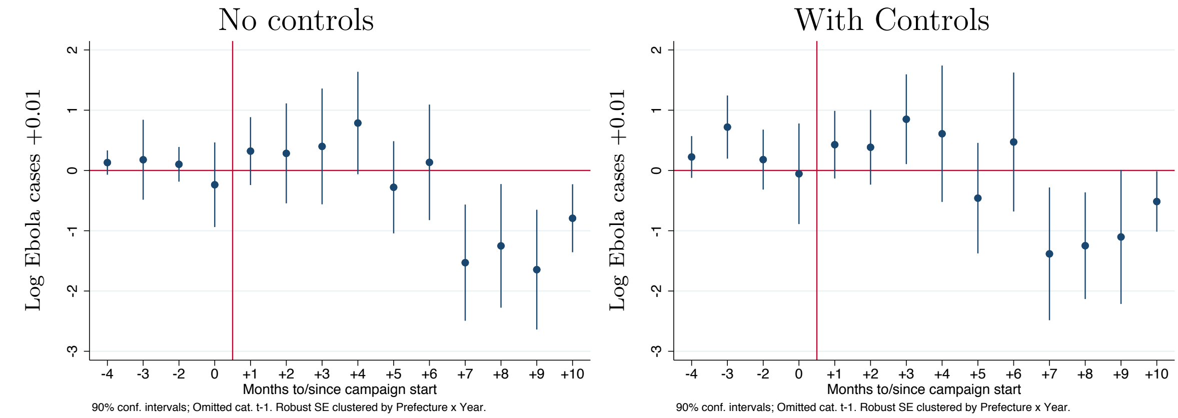
With Controls



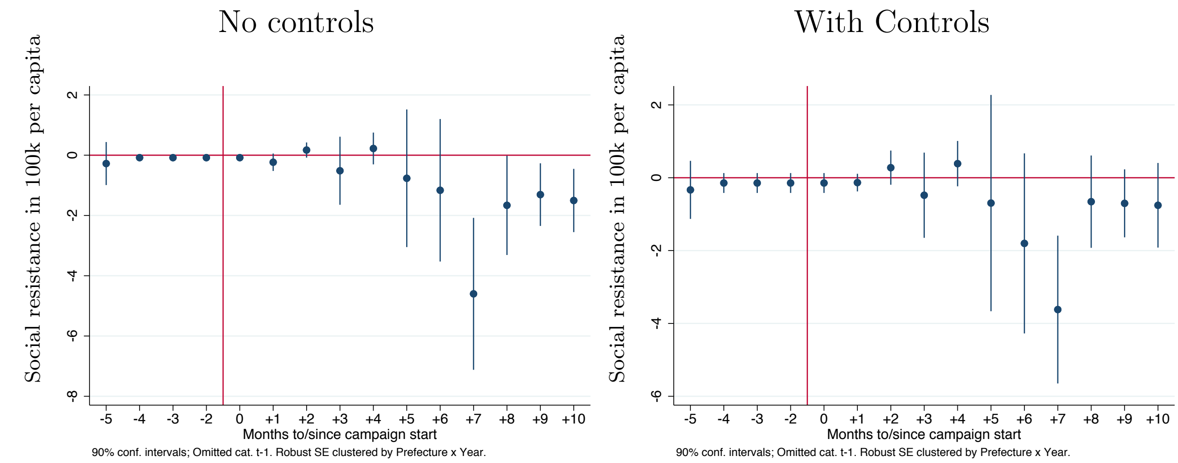
Notes: 90% confidence intervals. Robust Standard Errors clustered by Prefecture × Year. Controls: wealth level, education, rural, population, population^2, population-density; log-distance to epicenter, to the closest radio transmitter from any radio, national, private, rural, own rural radio (working and pre-existing), to the closest ETU, CCC and laboratory at each time × time-dummies.

Figure E.3: Event studies - Pre/Post Rural campaign by access to Own Community Rural Radio

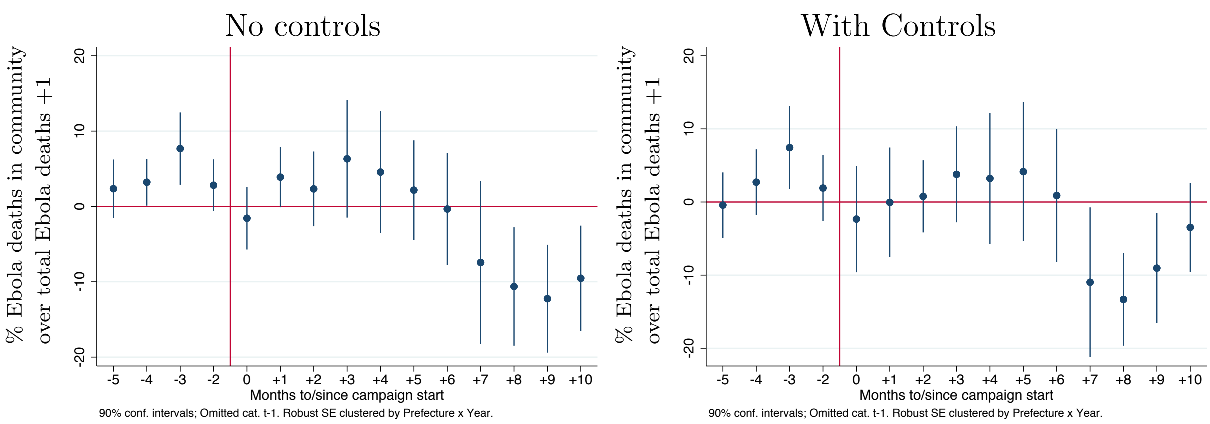
Lagged Dependent Variable Model - Log Ebola cases +0.01



Social resistance in 100'000 per capita



Treatment uptake (full sample)



Notes: 90% confidence intervals. Robust Standard Errors clustered by Prefecture × Year. Controls: wealth level, education, rural, population, population^2, population-density; log-distance to epicenter, to the closest radio transmitter from any radio, national, private, rural, own rural radio (working and pre-existing), to the closest ETU, CCC and laboratory at each time × time-dummies.

Table E.3: Event study - Outcome : Nr. of Ebola cases

	(1) ebola	(2) ebola	(3) ebola	(4) ebola	(5) ebola	(6) ebola
Own Rural × (t-5)	-0.243	-0.065	-0.237	-0.305	0.023	-0.259
	(0.358)	(0.443)	(0.454)	(0.389)	(0.347)	(0.774)
Own Rural × (t-4)	-0.119	0.054	0.018	-0.162	0.139	0.120
	(0.357)	(0.498)	(0.559)	(0.401)	(0.395)	(0.954)
Own Rural × (t-3)	-0.048	0.007	0.366	-0.057	0.020	0.580
	(0.429)	(0.439)	(0.638)	(0.479)	(0.386)	(0.967)
Own Rural × (t-2)	-0.360	-0.285	0.026	-0.404	-0.427	0.197
	(0.543)	(0.363)	(0.513)	(0.590)	(0.463)	(0.757)
Own Rural × (t)	-0.413	-0.489	-0.011	-0.184	-0.442	0.770
	(0.607)	(0.467)	(0.935)	(0.628)	(0.463)	(1.397)
Own Rural × (t+1)	-0.274	-0.317	-0.093	-0.308	-0.299	-0.768
	(0.445)	(0.411)	(0.467)	(0.507)	(0.407)	(0.564)
Own Rural × (t+2)	0.359	-0.214	1.249	0.445	0.057	1.431
	(1.207)	(0.801)	(1.563)	(1.509)	(0.985)	(1.398)
Own Rural × (t+3)	2.076	1.706	3.972	2.279	1.319	4.079**
	(2.453)	(1.463)	(3.057)	(2.723)	(1.933)	(1.809)
Own Rural × (t+4)	2.819	1.474	3.565	3.243	1.876	3.174
	(2.766)	(1.881)	(3.400)	(3.189)	(2.324)	(2.802)
Own Rural × (t+5)	3.070	1.764	3.354	3.715	2.644	2.885
	(1.960)	(1.674)	(2.474)	(2.334)	(1.905)	(2.639)
Own Rural × (t+6)	-0.117	-0.102	1.949	0.009	-0.336	2.373
	(2.322)	(1.998)	(2.199)	(2.776)	(2.095)	(3.056)
Own Rural × (t+7)	-2.747***	-1.994**	-2.016*	-2.638***	-2.313***	-1.713*
	(0.967)	(0.874)	(1.156)	(0.965)	(0.865)	(0.964)
Own Rural × (t+8)	-3.431**	-2.586*	-2.941*	-3.592**	-2.983**	-3.115**
	(1.384)	(1.358)	(1.606)	(1.438)	(1.328)	(1.487)
Own Rural × (t+9)	-4.732**	-3.829**	-4.081*	-4.980**	-4.317**	-3.916*
	(1.859)	(1.856)	(2.357)	(1.879)	(1.796)	(2.046)
Own Rural × (t+10)	-2.558**	-1.805*	-1.885	-2.708**	-2.082*	-1.797
	(1.182)	(1.008)	(1.283)	(1.238)	(1.080)	(1.086)
N	5376	5376	5376	4352	5376	4352
Mean (no Own Rural R.)	0.839	0.839	0.839	0.839	0.839	0.839
R-squared	0.31	0.35	0.32	0.33	0.31	0.48
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic		Y				Y
Dist.Tower			Y			Y
Demographic				Y		Y
ETU/Lab/CCC						Y
Trust Leader					Y	

(Robust SE) clustered by Prefecture × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.4: Event study - Outcome : ebola cases in 100'000 per capita

	(1)	(2)	(3)	(4)	(5)	(6)
Own Rural × (t-5)	-2.645	-1.773	-2.443	-2.422	-1.197	-1.987
	(2.124)	(2.384)	(2.644)	(2.153)	(1.828)	(3.068)
Own Rural × (t-4)	-2.353	-1.439	-1.865	-2.094	-0.880	-1.139
	(2.122)	(2.466)	(2.799)	(2.175)	(1.908)	(3.447)
Own Rural × (t-3)	-1.893	-1.710	-1.249	-1.503	-0.942	-0.444
	(2.204)	(2.355)	(2.833)	(2.248)	(1.825)	(3.397)
Own Rural × (t-2)	-2.041	-2.523	-2.140	-1.644	-1.520	-1.685
	(2.088)	(2.181)	(2.444)	(2.091)	(1.687)	(2.795)
Own Rural × (t)	-3.494	-3.616	-3.113	-1.355	-2.736	0.119
	(2.408)	(2.213)	(3.192)	(2.134)	(1.805)	(3.760)
Own Rural × (t+1)	-2.310	-2.673	-2.262	-1.952	-1.830	-2.611
	(2.213)	(2.346)	(2.583)	(2.279)	(1.836)	(2.936)
Own Rural × (t+2)	-0.324	-1.503	0.774	0.130	-0.492	1.541
	(2.690)	(2.475)	(3.674)	(3.703)	(2.361)	(3.783)
Own Rural × (t+3)	8.436	5.732	12.526	8.927	5.831	12.822*
	(8.723)	(6.670)	(11.961)	(9.623)	(6.550)	(7.372)
Own Rural × (t+4)	6.099	2.975	6.252	6.250	3.515	7.130
	(6.746)	(5.338)	(8.236)	(7.351)	(5.121)	(6.364)
Own Rural × (t+5)	4.595	2.324	3.668	5.558	2.882	7.070
	(4.804)	(4.564)	(5.259)	(5.675)	(4.072)	(5.782)
Own Rural × (t+6)	3.819	2.193	5.686	5.964	2.262	11.859
	(9.455)	(7.827)	(9.933)	(11.318)	(8.327)	(14.284)
Own Rural × (t+7)	-11.945**	-10.497**	-11.348**	-9.376**	-10.071**	-7.333**
	(4.516)	(4.034)	(4.757)	(3.951)	(4.157)	(3.411)
Own Rural × (t+8)	-12.034**	-10.532*	-12.287*	-10.727*	-10.230*	-10.388*
	(5.792)	(5.693)	(6.722)	(5.527)	(5.681)	(5.830)
Own Rural × (t+9)	-14.997**	-13.433*	-16.330*	-13.648**	-13.087*	-13.033*
	(7.407)	(7.084)	(8.927)	(6.667)	(7.211)	(6.861)
Own Rural × (t+10)	-9.638**	-7.716*	-8.516*	-8.957**	-7.511*	-6.046
	(4.377)	(3.973)	(4.717)	(4.237)	(3.970)	(3.714)
N	5376	5376	5376	4352	5376	4352
Mean (no Own Rural R.)	2.048	2.048	2.048	2.048	2.048	2.048
R-squared	0.19	0.22	0.20	0.21	0.20	0.29
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic		Y				Y
Dist.Tower			Y			Y
Demographic				Y		Y
ETU/Lab/CCC						Y
Trust Leader					Y	

(Robust SE) clustered by Prefecture × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.5: Event study - Outcome : Log ebola cases in 100'000 per capita +1

	(1)	(2)	(3)	(4)	(5)	(6)
Own Rural × (t-5)	-0.092	-0.053	-0.140	-0.159	-0.025	-0.192
	(0.149)	(0.158)	(0.176)	(0.148)	(0.129)	(0.180)
Own Rural × (t-4)	-0.031	-0.017	-0.038	-0.088	0.016	-0.066
	(0.147)	(0.163)	(0.185)	(0.149)	(0.134)	(0.204)
Own Rural × (t-3)	0.043	0.032	0.135	0.007	0.058	0.112
	(0.161)	(0.162)	(0.201)	(0.168)	(0.143)	(0.223)
Own Rural × (t-2)	0.019	-0.032	0.039	-0.021	-0.005	0.005
	(0.133)	(0.126)	(0.156)	(0.135)	(0.117)	(0.153)
Own Rural × (t)	-0.142	-0.171	-0.138	-0.120	-0.158	-0.064
	(0.127)	(0.129)	(0.164)	(0.133)	(0.106)	(0.211)
Own Rural × (t+1)	-0.005	-0.042	0.034	-0.049	-0.012	-0.084
	(0.155)	(0.155)	(0.183)	(0.174)	(0.136)	(0.204)
Own Rural × (t+2)	0.077	0.014	0.171	-0.001	-0.012	0.053
	(0.267)	(0.223)	(0.326)	(0.276)	(0.216)	(0.246)
Own Rural × (t+3)	0.235	0.143	0.447	0.145	0.092	0.366
	(0.413)	(0.314)	(0.483)	(0.427)	(0.309)	(0.297)
Own Rural × (t+4)	0.373	0.195	0.339	0.361	0.126	0.290
	(0.451)	(0.351)	(0.512)	(0.476)	(0.334)	(0.423)
Own Rural × (t+5)	0.175	-0.032	0.099	0.191	-0.007	0.044
	(0.389)	(0.345)	(0.460)	(0.427)	(0.325)	(0.399)
Own Rural × (t+6)	-0.063	-0.086	0.038	-0.123	-0.069	0.044
	(0.301)	(0.321)	(0.358)	(0.288)	(0.302)	(0.368)
Own Rural × (t+7)	-0.726**	-0.623**	-0.642*	-0.785***	-0.601**	-0.682**
	(0.317)	(0.299)	(0.355)	(0.276)	(0.295)	(0.279)
Own Rural × (t+8)	-0.955**	-0.769**	-0.955**	-0.975***	-0.799**	-0.919***
	(0.381)	(0.362)	(0.417)	(0.365)	(0.364)	(0.307)
Own Rural × (t+9)	-1.225***	-1.017**	-1.119**	-1.291***	-1.073**	-0.987**
	(0.443)	(0.413)	(0.551)	(0.427)	(0.424)	(0.397)
Own Rural × (t+10)	-0.958***	-0.770**	-0.767**	-1.029***	-0.781**	-0.686***
	(0.357)	(0.323)	(0.369)	(0.330)	(0.324)	(0.242)
N	5376	5376	5376	4352	5376	4352
Mean (no Own Rural R.)	0.248	0.248	0.248	0.248	0.248	0.248
R-squared	0.37	0.41	0.38	0.40	0.39	0.50
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic		Y				Y
Dist.Tower			Y			Y
Demographic				Y		Y
ETU/Lab/CCC						Y
Trust Leader					Y	

(Robust SE) clustered by Prefecture × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.6: Event study - Outcome : Log ebola cases +1

	(1) log(ebola)	(2) log(ebola)	(3) log(ebola)	(4) log(ebola)	(5) log(ebola)	(6) log(ebola)
Own Rural × (t-5)	-0.018	-0.014	-0.073	-0.048	0.021	-0.087
	(0.098)	(0.096)	(0.103)	(0.100)	(0.087)	(0.112)
Own Rural × (t-4)	0.016	0.016	0.002	-0.009	0.045	0.010
	(0.092)	(0.102)	(0.114)	(0.098)	(0.087)	(0.136)
Own Rural × (t-3)	0.020	0.040	0.114	0.003	0.023	0.126
	(0.109)	(0.099)	(0.128)	(0.119)	(0.099)	(0.151)
Own Rural × (t-2)	-0.017	-0.012	0.036	-0.040	-0.039	0.038
	(0.104)	(0.082)	(0.103)	(0.112)	(0.092)	(0.115)
Own Rural × (t)	-0.114	-0.108	-0.087	-0.095	-0.123	-0.012
	(0.098)	(0.093)	(0.123)	(0.103)	(0.081)	(0.165)
Own Rural × (t+1)	0.004	-0.001	0.049	-0.015	-0.005	-0.048
	(0.111)	(0.099)	(0.119)	(0.127)	(0.100)	(0.123)
Own Rural × (t+2)	-0.022	-0.028	0.088	-0.058	-0.069	0.037
	(0.170)	(0.136)	(0.196)	(0.186)	(0.146)	(0.162)
Own Rural × (t+3)	0.136	0.119	0.366	0.104	0.048	0.323
	(0.290)	(0.194)	(0.328)	(0.311)	(0.231)	(0.204)
Own Rural × (t+4)	0.276	0.183	0.347	0.294	0.137	0.299
	(0.320)	(0.237)	(0.360)	(0.348)	(0.254)	(0.318)
Own Rural × (t+5)	0.244	0.096	0.272	0.286	0.143	0.208
	(0.258)	(0.223)	(0.310)	(0.299)	(0.225)	(0.292)
Own Rural × (t+6)	-0.034	-0.060	0.148	-0.058	-0.040	0.086
	(0.223)	(0.233)	(0.243)	(0.236)	(0.226)	(0.270)
Own Rural × (t+7)	-0.492**	-0.411**	-0.373*	-0.524***	-0.408**	-0.401**
	(0.187)	(0.184)	(0.210)	(0.173)	(0.172)	(0.182)
Own Rural × (t+8)	-0.648***	-0.493**	-0.586**	-0.679***	-0.549**	-0.600***
	(0.233)	(0.229)	(0.261)	(0.230)	(0.221)	(0.206)
Own Rural × (t+9)	-0.854***	-0.676**	-0.712**	-0.915***	-0.759***	-0.649**
	(0.283)	(0.269)	(0.355)	(0.280)	(0.269)	(0.258)
Own Rural × (t+10)	-0.640***	-0.493**	-0.465*	-0.690***	-0.527**	-0.438***
	(0.225)	(0.203)	(0.233)	(0.219)	(0.204)	(0.159)
N	5376	5376	5376	4352	5376	4352
Mean (no Own Rural R.)	0.195	0.195	0.195	0.195	0.195	0.195
R-squared	0.47	0.51	0.48	0.50	0.48	0.59
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic		Y				Y
Dist.Tower			Y			Y
Demographic				Y		Y
ETU/Lab/CCC						Y
Trust Leader					Y	

(Robust SE) clustered by Prefecture × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.7: Event study - Lagged Dependent Variable Model - Outcome : log(Ebola+0, 01)

	(1)	(2)	(3)	(4)	(5)	(6)
Own Rural × (t-4)	0.131	-0.020	0.215	0.162	-0.001	0.224
	(0.121)	(0.084)	(0.135)	(0.131)	(0.083)	(0.208)
Own Rural × (t-3)	0.178	0.171	0.692***	0.244	0.028	0.720**
	(0.398)	(0.188)	(0.254)	(0.417)	(0.382)	(0.314)
Own Rural × (t-2)	0.102	-0.073	0.127	0.141	-0.118	0.180
	(0.172)	(0.260)	(0.189)	(0.201)	(0.203)	(0.298)
Own Rural × (t)	-0.237	-0.336	-0.188	-0.150	-0.430	-0.055
	(0.421)	(0.462)	(0.486)	(0.394)	(0.382)	(0.500)
Own Rural × (t+1)	0.321	0.132	0.594*	0.304	0.162	0.428
	(0.338)	(0.244)	(0.347)	(0.328)	(0.308)	(0.336)
Own Rural × (t+2)	0.284	0.140	0.483	0.216	-0.072	0.385
	(0.497)	(0.371)	(0.549)	(0.485)	(0.390)	(0.372)
Own Rural × (t+3)	0.399	0.108	0.837	0.380	0.050	0.850*
	(0.576)	(0.411)	(0.610)	(0.598)	(0.449)	(0.447)
Own Rural × (t+4)	0.787	0.368	0.565	1.025*	0.256	0.609
	(0.510)	(0.396)	(0.661)	(0.565)	(0.453)	(0.678)
Own Rural × (t+5)	-0.279	-0.620	-0.406	-0.186	-0.585	-0.459
	(0.458)	(0.436)	(0.581)	(0.503)	(0.471)	(0.550)
Own Rural × (t+6)	0.135	0.135	0.544	0.064	0.258	0.472
	(0.575)	(0.600)	(0.651)	(0.564)	(0.581)	(0.691)
Own Rural × (t+7)	-1.530**	-1.368**	-1.191*	-1.579***	-1.341**	-1.383**
	(0.578)	(0.598)	(0.687)	(0.498)	(0.578)	(0.660)
Own Rural × (t+8)	-1.251**	-1.108*	-1.287**	-1.145*	-1.166*	-1.248**
	(0.615)	(0.614)	(0.639)	(0.644)	(0.585)	(0.531)
Own Rural × (t+9)	-1.645***	-1.521**	-1.248	-1.751***	-1.630***	-1.103
	(0.596)	(0.617)	(0.782)	(0.608)	(0.596)	(0.667)
Own Rural × (t+10)	-0.793**	-0.873**	-0.334	-0.859***	-0.701**	-0.515*
	(0.338)	(0.350)	(0.251)	(0.315)	(0.298)	(0.300)
N	5040	5040	5040	4080	5040	4080
Mean (no Own Rural R.)	-3.829	-3.829	-3.829	-3.829	-3.829	-3.829
R-squared	0.45	0.48	0.47	0.48	0.46	0.55
Lagged Dep.Var.	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic		Y				Y
Dist.Tower			Y			Y
Demographic				Y		Y
ETU/Lab/CCC						Y
Trust Leader					Y	

(Robust SE) clustered by Prefecture × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.8: Event study - Outcome : Social resistance in 100'000 per capita

	(1) Resistance	(2) Resistance	(3) Resistance	(4) Resistance	(5) Resistance	(6) Resistance
Own Rural × (t-5)	-0.277	-0.201	-0.372	-0.327	-0.275	-0.333
	(0.428)	(0.381)	(0.629)	(0.424)	(0.444)	(0.478)
Own Rural × (t-4)	-0.082	-0.081	-0.127*	0.000	-0.065	-0.145
	(0.063)	(0.060)	(0.071)	(0.000)	(0.052)	(0.163)
Own Rural × (t-3)	-0.082	-0.081	-0.127*	0.000	-0.065	-0.145
	(0.063)	(0.060)	(0.071)	(.)	(0.052)	(0.163)
Own Rural × (t-2)	-0.082	-0.081	-0.127*	0.000	-0.065	-0.145
	(0.063)	(0.060)	(0.071)	(.)	(0.052)	(0.163)
Own Rural × (t)	-0.082	-0.081	-0.127*	0.000	-0.065	-0.145
	(0.063)	(0.060)	(0.071)	(.)	(0.052)	(0.163)
Own Rural × (t+1)	-0.233	-0.210	-0.296	0.000	-0.193	-0.133
	(0.173)	(0.146)	(0.193)	(.)	(0.144)	(0.145)
Own Rural × (t+2)	0.171	0.130	0.228	0.304	0.112	0.276
	(0.151)	(0.132)	(0.255)	(0.229)	(0.119)	(0.281)
Own Rural × (t+3)	-0.516	-0.492	-0.260	-0.651	-1.124	-0.480
	(0.677)	(0.591)	(0.700)	(0.881)	(0.718)	(0.701)
Own Rural × (t+4)	0.223	0.091	0.133	0.446	-0.152	0.387
	(0.316)	(0.274)	(0.356)	(0.408)	(0.234)	(0.373)
Own Rural × (t+5)	-0.766	-0.741	-1.073	-0.765	-1.113	-0.696
	(1.369)	(1.335)	(1.702)	(1.530)	(1.462)	(1.780)
Own Rural × (t+6)	-1.164	-0.992	-1.703	-1.748	-1.055	-1.803
	(1.418)	(1.370)	(2.133)	(1.541)	(1.540)	(1.482)
Own Rural × (t+7)	-4.601***	-4.271***	-3.563**	-5.007***	-4.401***	-3.619***
	(1.511)	(1.274)	(1.730)	(1.709)	(1.545)	(1.216)
Own Rural × (t+8)	-1.663*	-1.544*	-1.371	-1.467	-1.558	-0.657
	(0.988)	(0.871)	(0.907)	(1.014)	(0.935)	(0.760)
Own Rural × (t+9)	-1.308**	-1.279**	-0.915	-1.423**	-1.189*	-0.703
	(0.623)	(0.577)	(0.571)	(0.712)	(0.633)	(0.560)
Own Rural × (t+10)	-1.503**	-1.323**	-0.930	-1.564**	-1.227*	-0.756
	(0.629)	(0.558)	(0.706)	(0.744)	(0.616)	(0.696)
N	5376	5376	5376	4352	5376	4352
Mean (no Own Rural R.)	0.698	0.698	0.698	0.698	0.698	0.698
R-squared	0.29	0.31	0.31	0.33	0.29	0.42
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic		Y				Y
Dist.Tower			Y			Y
Demographic				Y		Y
ETU/Lab/CCC						Y
Trust Leader					Y	

(Robust SE) clustered by Prefecture × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.9: Pre-Trends (pre-Rural Radio campaign) - Dependent variable : log(Ebola+0.01)

	(1)	(2)	(3)	(4)	(5)	(6)
Own Rural × Trend	-0.02	-0.00	-0.02	-0.01	0.00	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
N	1956	1956	1956	1572	1956	1572
Mean (no Own Rural R.)	-4.43	-4.43	-4.43	-4.43	-4.43	-4.43
R-squared	0.46	0.48	0.46	0.48	0.49	0.51
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic.		Y			Y	Y
Dist.Tower			Y			Y
Demographic				Y	Y	Y
ETU/Labs/CCC					Y	Y

(Robust SE) clustered by Prefecture × Year. Excluding first Prefecture hit by Ebola.
Omitted: Other Radios × Trend
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.10: Pre-Trends (pre-Rural Radio campaign) - Full sample
Dependent variable : log(Ebola+0.01)

	(1)	(2)	(3)	(4)	(5)	(6)
Any Radio × Trend	-0.03	-0.01	-0.03	-0.05*	-0.01	-0.02
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
National × Trend	0.01	-0.00	0.01	0.03	-0.00	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Private-Urtelgui × Trend	0.01	-0.00	0.01	-0.00	-0.02	-0.03
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Any Rural × Trend	0.06*	0.03	0.06*	0.06**	0.04*	0.04**
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Own Rural × Trend	-0.02	-0.00	-0.02	-0.01	0.00	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
N	1956	1956	1956	1572	1956	1572
Mean (no Own Rural R.)	-4.43	-4.43	-4.43	-4.43	-4.43	-4.43
R-squared	0.46	0.48	0.46	0.48	0.49	0.51
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic.		Y			Y	Y
Dist.Tower			Y			Y
Demographic				Y	Y	Y
ETU/Labs/CCC					Y	Y

(Robust SE) clustered by Prefecture × Year. Excluding first Prefecture hit by Ebola.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.11: Difference-in-Differences - Full sample
Dependent variable : log(Ebola+0.01)

	(1)	(2)	(3)	(4)	(5)	(6)
Any Radio × Post Rural	-0.24	-0.09	-0.24	-0.02	0.31	0.26
	(0.46)	(0.44)	(0.46)	(0.49)	(0.48)	(0.48)
National × Post Rural	0.01	-0.29	0.01	-0.05	-0.56	-0.42
	(0.45)	(0.38)	(0.45)	(0.48)	(0.34)	(0.36)
Private-Urtelgui × Post Rural	0.75***	0.87**	0.75***	0.76**	1.22***	1.23***
	(0.28)	(0.41)	(0.28)	(0.32)	(0.35)	(0.35)
Any Rural × Post Rural	0.51	0.35	0.51	0.30	0.04	-0.06
	(0.44)	(0.42)	(0.44)	(0.44)	(0.40)	(0.43)
Own Rural × Post Rural	-0.38	-0.24	-0.38	-0.42	-0.43	-0.25
	(0.34)	(0.32)	(0.34)	(0.34)	(0.27)	(0.37)
N	9744	9744	9744	7888	7888	7888
Mean (no Own Rural R.)	-4.31	-4.31	-4.31	-4.31	-4.31	-4.31
R-squared	0.28	0.28	0.28	0.29	0.33	0.33
Subpref FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Pop/Dens/Dist.Epic.		Y			Y	Y
Dist.Tower			Y			Y
Demographic				Y	Y	Y
ETU/Labs/CCC					Y	Y

(Robust SE) clustered by Prefecture × Year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Average number of Ebola cases for the sub-sample (with no access to rural radios): 0.36. The coefficients can be interpreted as the approximate percentage change in the number of Ebola cases due to a 1 *pp* increase in access to a local radio. This is approximately $(e^{\hat{\beta}} \times 0.01 - 1) \times \frac{0.37}{0.36} \times 100\%$.

Table E.12: Balancing Test for population, area and distance to epicenter

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Population	0.064***	0.052*	0.151***	0.121***	0.087***	0.082**	0.029
	(0.022)	(0.028)	(0.028)	(0.030)	(0.025)	(0.033)	(0.029)
Geographic Area	-0.147***	-0.121***	-0.073***	-0.063***	-0.117***	-0.051***	0.023**
	(0.016)	(0.013)	(0.012)	(0.012)	(0.016)	(0.014)	(0.011)
Distance to Epicenter	-0.002	0.040**	0.004	0.001	-0.008	-0.027*	-0.022
	(0.005)	(0.019)	(0.008)	(0.009)	(0.006)	(0.015)	(0.015)
Any Radio							0.073
							(0.094)
Any Rural Radio							0.551***
							(0.108)
N	331	331	331	331	331	332	331
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (all)	0.00	0.00	0.00	0.00	0.00	0.00	0.04

(Robust SE)
Excl. capital
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: *Geographic area* is a standardized variable measuring the area of a sub-prefecture. *Population* is log-population. *Distance to epicenter* is the log-distance to the start of the Ebola outbreak.

Table E.13: Balancing Test for covariates

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Income group	-0.021	-0.045	-0.110*	-0.048	0.009	-0.075	-0.081
	(0.091)	(0.073)	(0.060)	(0.063)	(0.047)	(0.088)	(0.081)
Education	0.037	-0.095	0.010	-0.006	0.017	0.040	0.029
	(0.081)	(0.063)	(0.050)	(0.051)	(0.040)	(0.067)	(0.064)
Rural Area	-0.346***	-0.094	-0.282***	-0.205**	0.027	-0.001	-0.018
	(0.107)	(0.107)	(0.105)	(0.099)	(0.058)	(0.112)	(0.098)
Religion	-0.003	-0.022***	-0.025**	-0.028**	0.001	-0.010	-0.011
	(0.014)	(0.008)	(0.011)	(0.011)	(0.005)	(0.012)	(0.011)
Strong Religious beliefs	0.086	0.283*	0.095	0.117	-0.036	-0.087	-0.065
	(0.192)	(0.142)	(0.134)	(0.126)	(0.085)	(0.150)	(0.125)
Electricity	0.154	0.066	0.129	0.234	-0.037	-0.281	-0.258
	(0.169)	(0.195)	(0.171)	(0.178)	(0.099)	(0.231)	(0.232)
Piped water	-0.130	-0.211**	-0.128	-0.080	0.087	0.196**	0.141
	(0.117)	(0.097)	(0.084)	(0.073)	(0.055)	(0.093)	(0.090)
Health facility	-0.155	-0.192	-0.029	-0.091	-0.050	-0.133	-0.102
	(0.126)	(0.151)	(0.096)	(0.104)	(0.069)	(0.140)	(0.129)
Market	0.156	0.141	-0.045	-0.003	0.031	-0.020	-0.039
	(0.105)	(0.109)	(0.079)	(0.076)	(0.058)	(0.112)	(0.095)
Police	0.022	-0.118	0.340**	0.332**	0.051	-0.232	-0.264
	(0.186)	(0.201)	(0.136)	(0.146)	(0.086)	(0.244)	(0.248)
Any Radio		0.481***	0.365***	0.322***	0.898***	0.607***	0.040
		(0.090)	(0.079)	(0.074)	(0.053)	(0.103)	(0.281)
Any Rural Radio							0.631**
							(0.290)
N	99	99	99	99	99	99	99
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (all cov.)	0.00	0.00	0.00	0.00	0.59	0.07	0.12
p-val (sum cov.)	0.57	0.42	0.87	0.43	0.62	0.14	0.07

(Robust SE)

Excl. capital

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.14: Balancing Test for disease prevalence in 2013 (cases per cap. in 1000)

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Flu	1.238***	-0.641**	-0.046	-0.115	0.490*	-0.943	-1.261
	(0.338)	(0.293)	(1.159)	(1.150)	(0.261)	(1.025)	(1.031)
Tetanus	3.826	-66.478**	30.499	15.589	10.706	39.837	32.910
	(33.391)	(31.903)	(71.812)	(70.364)	(25.392)	(81.592)	(74.326)
Measels	24.827	-47.157*	-17.176	-13.291	2.507	-3.878	-5.500
	(26.016)	(24.805)	(29.854)	(26.991)	(16.456)	(42.677)	(38.229)
Polio	3.715	-72.735	-16.514	-35.766	-14.022	41.688	50.761
	(57.371)	(52.947)	(69.723)	(58.526)	(38.108)	(80.858)	(65.694)
Malaria	-0.004	0.004	-0.007	0.001	-0.002	-0.007	-0.006
	(0.012)	(0.010)	(0.014)	(0.011)	(0.008)	(0.016)	(0.013)
Meningitis	-6.748	-2.745	-3.986	-2.784	0.227	8.379	8.232
	(5.276)	(4.445)	(9.230)	(9.333)	(4.021)	(7.640)	(6.443)
Yellow Fever	12.528	63.333*	-27.750	-20.959	-5.160	-15.848	-12.508
	(27.699)	(35.445)	(30.003)	(25.543)	(21.442)	(55.269)	(47.104)
Diarrhea	0.221	1.054***	-0.677	-0.597	-0.111	-0.337	-0.265
	(0.509)	(0.369)	(0.566)	(0.576)	(0.280)	(0.540)	(0.447)
Cholera	3.679	-0.399	5.456	4.788	0.971	-9.454	-10.082
	(6.197)	(6.846)	(4.896)	(4.967)	(2.582)	(6.950)	(7.371)
Any Radio		0.731***	0.764***	0.825***	0.872***	0.292	-0.273
		(0.157)	(0.245)	(0.222)	(0.131)	(0.272)	(0.467)
Any Rural Radio							0.647
							(0.495)
N	33	33	33	33	33	33	33
Mean	0.657	0.292	0.237	0.213	0.477	0.259	0.259
p-val (all diseases)	0.00	0.00	0.01	0.05	0.30	0.44	0.31
p-val (sum diseases)	0.44	0.02	0.73	0.50	0.90	0.52	0.45

(Robust SE)

Excluding capital. Diseases in 2013.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.15: In areas with higher access to a radio signal (from any radio), more people own radio devices

	(1) Owns Radio	(2) Urban	(3) Owns Radio	(4) Urban	(5) Owns Radio	(6) Urban	(7) Owns Radio	(8) Urban	(9) Owns Radio	(10) Urban
Any Radio	0.204***	1.107***	0.161	0.763*	0.162***	1.077***	0.166*	1.121***	0.132*	0.898***
	(0.053)	(0.097)	(0.104)	(0.334)	(0.051)	(0.109)	(0.071)	(0.140)	(0.065)	(0.134)
Rural			0.044	0.354						
			(0.092)	(0.306)						
Own Rural					0.065*	0.046				
					(0.030)	(0.085)				
National							0.040	-0.014		
							(0.048)	(0.106)		
Private									0.080*	0.231*
									(0.046)	(0.098)
N	2459	2459	2459	2459	2459	2459	2459	2459	2459	2459
Mean	0.768	0.572	0.768	0.572	0.768	0.572	0.768	0.572	0.768	0.572
P(Sum Coef=0)			0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust SE Clustered by Sub-Prefecture

* $p < 0.10$, * $p < 0.05$, *** $p < 0.01$

Data source: INS Guinea Post-Ebola survey, 2015

Table E.16: Own Community Rural Radio as a predictor of listening to that Radio

	Listen To Rural Radio				Listen To Rural Radio				Listen To Rural Radio			
	(1) Gral	(2) Gral	(3) Eb-Prog	(4) Eb-Prog	(5) Gral	(6) Gral	(7) Eb-Prog	(8) Eb-Prog	(9) Gral	(10) Gral	(11) Eb-Prog	(12) Eb-Prog
Any Rural Radio	0.0243	-0.00391	0.00690	-0.0126								
	(0.0234)	(0.0499)	(0.0285)	(0.0591)								
Own Rural Radio					0.0556***	0.0592***	0.0585	0.0448				
					(0.0126)	(0.0151)	(0.0364)	(0.0353)				
New Own Rural Radio									0.0424***	0.0396**	0.00316	-0.00917
									(0.0134)	(0.0151)	(0.0308)	(0.0214)
N	506	506	506	506	506	506	506	506	506	506	506	506
Mean	0.0382	0.0382	0.0361	0.0361	0.0382	0.0382	0.0361	0.0361	0.0382	0.0382	0.0361	0.0361
Controls	Pop	All	Pop	All	Pop	All	Pop	All	Pop	All	Pop	All

(Robust SE) clustered by Sub-Prefecture. Sample: 34 Sub-prefectures. Excluding capital.

Controls: N, pop, popdens, wealth index, educ, urban.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Internews Survey (2015)

Notes: The Ebola program studied here is "Ebola Chrono" a campaign aired in different media outlets that started in January 2015.

Table E.17: Private Radio signal reception as a predictor of listening to a Private radio

	Listen To Priv. Radio				Listen To Priv. Radio				Listen To Priv. Radio			
	(1) Gral	(2) Gral	(3) Eb-Prog	(4) Eb-Prog	(5) Gral	(6) Gral	(7) Eb-Prog	(8) Eb-Prog	(9) Gral	(10) Gral	(11) Eb-Prog	(12) Eb-Prog
Private	0.187	0.285***	0.00535	0.0129								
	(0.131)	(0.104)	(0.123)	(0.142)								
Private-Urtelgui					0.133	0.183**	0.0599	0.0599	0.136	0.237***	0.0597	0.0660
					(0.0900)	(0.0853)	(0.0825)	(0.110)	(0.0972)	(0.0726)	(0.0827)	(0.121)
Private-Non Urtelgui									-0.0274	-0.246***	0.00205	-0.0277
									(0.0881)	(0.0810)	(0.0531)	(0.0950)
N	506	506	506	506	506	506	506	506	506	506	506	506
Mean	0.455	0.455	0.490	0.490	0.455	0.455	0.490	0.490	0.455	0.455	0.490	0.490
Controls	Pop	All	Pop	All	Pop	All	Pop	All	Pop	All	Pop	All

(Robust SE) clustered by Sub-Prefecture. Sample: 34 Sub-prefectures. Excluding capital.
Controls: N, pop, popdens, wealth index, educ, urban.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Internews Survey (2015)

Notes: The Ebola program studied here is "Ebola Chrono" a campaign aired in different media outlets that started in January 2015.

Table E.18: National or International Radio signal reception as predictors of listening to either radio

	Listen To National Radio				Listen To National Radio				Listen To International Radio			
	(1) Gral	(2) Gral	(3) Eb-Prog	(4) Eb-Prog	(5) Gral	(6) Gral	(7) Eb-Prog	(8) Eb-Prog	(9) Gral	(10) Gral	(11) Eb-Prog	(12) Eb-Prog
National	-0.0220	-0.0197	0.0792**	0.0720**	0.0409	0.0463	0.102**	0.0981**				
	(0.0252)	(0.0168)	(0.0344)	(0.0300)	(0.0315)	(0.0297)	(0.0428)	(0.0392)				
International Radio									0.0280**	0.0258*	0.0240*	0.0218**
									(0.0126)	(0.0133)	(0.0119)	(0.00958)
N	506	506	506	506	506	506	506	506	506	506	506	506
Mean	0.0746	0.0746	0.164	0.164	0.0746	0.0746	0.164	0.164	0.0195	0.0195	0.0150	0.0150
Contr. access to Any Radio					Y	Y	Y	Y	Y	Y	Y	Y
Controls	Pop	All	Pop	All	Pop	All	Pop	All	Pop	All	Pop	All

(Robust SE) clustered by Sub-Prefecture. Sample: 34 Sub-prefectures. Excluding capital.

Controls: N, pop, popdens, wealth index, educ, urban.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Internews Survey (2015)

Notes: The Ebola program studied here is "Ebola Chrono" a campaign aired in different media outlets that started in January 2015.

Table E.19: Ownership of radio-devices predicts having heard about Ebola on the Media

	Ebola on Media			Heard about Ebola			Ebola Knowledge		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Owns a Radio	0.123***	0.101***	0.101***	0.00436	0.00368	0.00374	0.0176	0.0203	0.0205
	(0.0317)	(0.0270)	(0.0270)	(0.00510)	(0.00528)	(0.00527)	(0.0217)	(0.0202)	(0.0202)
Dist. Epic.			-0.0106			0.00389			0.00851
			(0.0121)			(0.00255)			(0.00878)
N	2447	2447	2447	2447	2447	2447	2447	2447	2447
Mean	0.71	0.71	0.71	0.99	0.99	0.99	2.90	2.90	2.90
R-squared	0.06	0.12	0.12	0.02	0.04	0.04	0.04	0.07	0.07
Controls		Y	Y		Y	Y		Y	Y
Cond_mean									

(Robust SE) clustered by Sub-prefecture. With Region FE.

Controls: pop, dist. epic., wealth, educ, gender, elect, water, health fac., urban

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS).

Table E.20: Dep. Var: Owns Radio Device

	(1)	(2)	(3)	(4)	(5)	(6)
Own Rural Radio ϕ	0.127***	0.179***	0.0966***	0.193**	0.104***	0.166
	(0.0329)	(0.0440)	(0.0343)	(0.0754)	(0.0302)	(0.159)
N	2447	1234	1234	1234	1234	1234
Mean	0.77	0.79				
R-squared	0.02	0.04	0.10	0.10	0.10	0.10
F-test ϕ	14.79	16.65	7.95	6.55	11.85	1.09
Controls			Y	Y	Y	Y
Distance to Transmitter ϕ				Y		Y
Distance to Rural Radio Transmitter					Y	Y
Other Radio Signals						Y
Cond. Rural Radio > median		Y	Y	Y	Y	Y

(Robust SE) clustered by Sub-prefecture. With Region FE.

Controls: pop, dist. epic., wealth, educ, gender, elect, water, health fac., urban

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS).

Table E.21: First Stage - Dep. Var: Heard about Ebola on the Media

	(1)	(2)	(3)	(4)	(5)	(6)
Own Rural Radio ϕ	0.117	0.594***	0.394***	0.242**	0.397***	0.472**
	(0.0805)	(0.127)	(0.0431)	(0.0982)	(0.0438)	(0.185)
N	2447	1234	1234	1234	1234	1234
Mean	0.71	0.68				
R-squared	0.05	0.11	0.24	0.24	0.24	0.24
F-test ϕ	2.10	21.97	83.62	6.10	81.96	6.53
Controls			Y	Y	Y	Y
Distance to Transmitter ϕ				Y		Y
Distance to Rural Radio Transmitter					Y	Y
Other Radio Signals						Y
Cond. Rural Radio > median		Y	Y	Y	Y	Y

(Robust SE) clustered by Sub-prefecture. With Region FE.
Controls: pop, dist. epic., wealth, educ, gender, elect, water, health fac., urban
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS).

Table E.22: First Stage - Dep. Var: Heard about Ebola on the Media

	(1)	(2)	(3)	(4)	(5)	(6)
Ebola Any Info	0.805***	0.787***	0.781***	0.784***	0.787***	0.815***
	(0.0273)	(0.0388)	(0.0425)	(0.0434)	(0.0449)	(0.0424)
Own Rural Radio ϕ	0.0596	0.131	0.0600	-0.157	0.0662	0.320**
	(0.0499)	(0.101)	(0.0607)	(0.143)	(0.0678)	(0.142)
N	2447	1234	1234	1234	1234	1234
Mean	0.71	0.68				
R-squared	0.37	0.37	0.43	0.43	0.43	0.44
F-test ϕ	1.43	1.68	0.98	1.21	0.95	5.08
Controls			Y	Y	Y	Y
Distance to Transmitter ϕ				Y		Y
Distance to Rural Radio Transmitter					Y	Y
Other Radio Signals						Y
Cond. Rural Radio > median		Y	Y	Y	Y	Y

(Robust SE) clustered by Sub-prefecture. With Region FE.
Controls: pop, dist. epic., wealth, educ, gender, elect, water, health fac., urban
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS).

Table E.23: OLS : Having heard about Ebola on the Media

Outcome: Neighbors Seek Treatment...

	(1) In 2013	(2) In 2015	(3) Fear to seek	(4) Like/More than 2013	(5) Like/More/Less than 2013
Ebola Any Info	0.0741***	-0.256***	-0.153**	-0.0224	-0.210*
	(0.0275)	(0.0814)	(0.0606)	(0.0465)	(0.112)
Ebola Info on Radio/TV	-0.0444	0.123***	0.00787	0.151***	0.242***
	(0.0279)	(0.0300)	(0.0121)	(0.0341)	(0.0516)
Dist. Epic.	0.00561***	0.0169	-0.00310	0.0225	0.0476
	(0.00193)	(0.0158)	(0.0137)	(0.0164)	(0.0325)
N	2447	2247	2443	2447	2247
Mean	0.92	0.52	0.05	0.28	-0.25
R-squared	0.07	0.24	0.23	0.14	0.22
Controls	Y	Y	Y	Y	Y

(Robust SE) clustered by Sub-prefecture. With Region FE.
Controls: pop, dist. epic., wealth, educ, gender, elect, water, health fac., urban
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

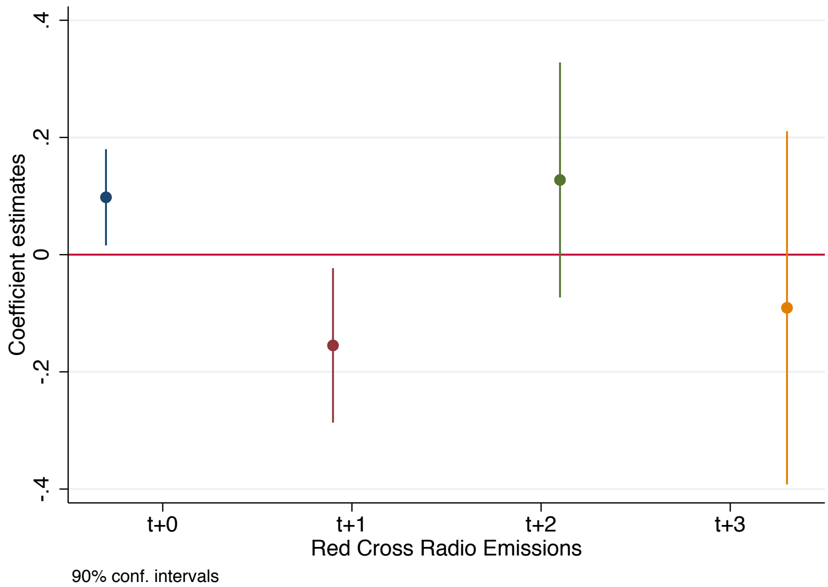
Data source: Post-Ebola survey (2015), Guinean National Institute of Statistics (INS). *In 2013*: neighbors sought treatment in 2013? yes (1), no (0). *In 2015*: neighbors sought treatment in 2015? yes (1), no (0). *Fear to seek*: are you scared of going to treatment centers? *Like/More than 2013*: neighbors sought treatment in 2013 but not in 2015 (0), otherwise (1). *Like/More/Less than 2013*: neighbors seek more (1) equal (0) less (-1) treatment in 2015 than in 2013.

Table E.24: What do you like about the Ebola Radio show "Ebola Chrono"?

	Mean	(Std. Dev.)	Observations
What did you like about the program? (Choose one)			
Like Info	0.44	(0.50)	863
Like Presenters	0.11	(0.31)	863
Like Expert Interviews	0.19	(0.39)	863
Like Citizen Interviews	0.20	(0.40)	863
Like Music	0.06	(0.24)	863
What did you learn from the program? (Choose one)			
Learned about Ebola	0.13	(0.33)	863
Learned about Prevention	0.54	(0.50)	863
Learned about Cures	0.33	(0.47)	863
Did the program influence...? (Yes/No)			
Health outcomes	0.80	(0.40)	863
Ebola outcomes	0.78	(0.41)	863
Did you find this information useful? (Yes/No)			
On other Diseases	0.86	(0.34)	1000
On Ebola victims	0.72	(0.45)	1000
On Preventing Ebola	0.92	(0.27)	1000
On Government	0.83	(0.38)	1000
Observations	1000		

Data source: Internews Survey (2015)

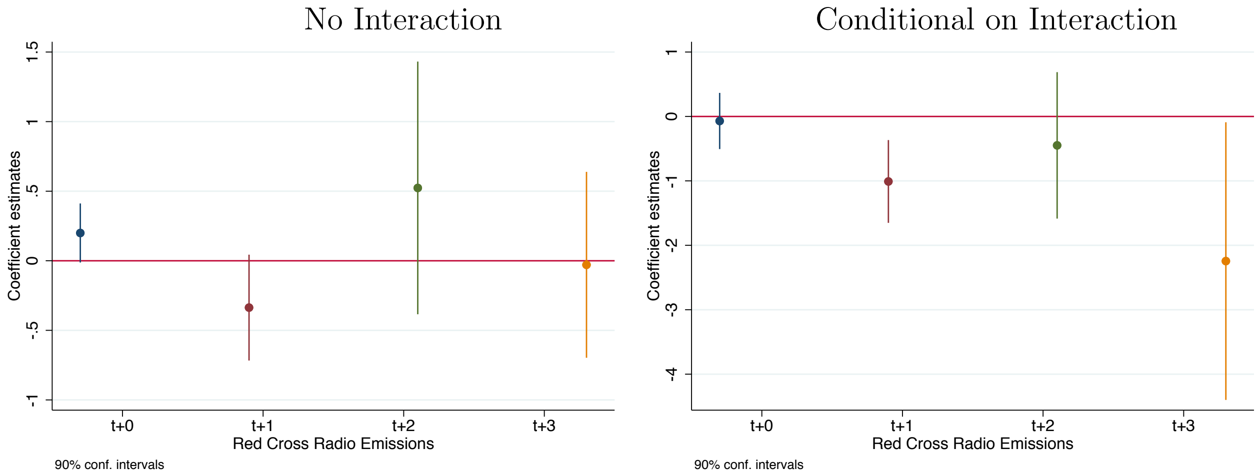
Figure E.4: Refused burials in 100k per capita - no interaction term



Data source: International Federation of the Red Cross in Guinea, April-December, 2015

The outcome variables are *total refused burials*, an average of 0.33 per month, and *refused burials* in 100'000 per capita, with monthly mean (std. dev.) 0.11 (0.39). *Red Cross Radio* are the number of radio emissions aired and here we standardized the original variable which had mean (std. dev.) 0.85 (3.29). Plotted coefficients are separate regressions, conditional on social mobilization campaigns, as well as conditional on demographic controls, social mobilization and other efforts by the Red Cross. However, we do not include the interaction term of radio emissions with preventive social mobilization campaigns. Table available upon request.

Figure E.5: % of Refused burials over Total Burials



Data source: International Federation of the Red Cross in Guinea, April-December, 2015

The outcome variable is (*refused burials / total safe and dignified burials*+1) $\times$100, with a monthly mean (std. dev.) 0.71 (4.40). The average number of total burials for a prefecture in a given month is 71, which include Ebola-related and non-Ebola related burials conducted by the Red Cross. *Red Cross Radio* are the number of radio emissions aired and here we standardized the original variable which had mean (std. dev.) 0.85 (3.29). Plotted coefficients are from separate regressions, conditional on demographic controls, social mobilization and other efforts by the Red Cross. The right graph includes the interaction term *Red Cross Radio*$\times$*Social Mob. Preventive.*

Table E.25: Refused Burials $t + 1$

Outcome: Refused burials in 100'000 per capita

	(1) t+1	(2) t+1	(3) t+1	(4) t+1	(5) t+1	(6) t+1	(7) t+1
Red Cross Radio	-0.013	-0.080	-0.105*	0.012	-0.090	-0.155*	-0.326***
	(0.064)	(0.056)	(0.059)	(0.056)	(0.077)	(0.080)	(0.108)
Red Cross Radio × Social Mobilis. Preventive							-0.010
							(0.034)
Social Mobilis. Preventive				-0.093**	-0.066	-0.041	0.227***
				(0.040)	(0.042)	(0.036)	(0.085)
Social Mobilis. Response				0.043	-0.095	-0.193	-0.270*
				(0.136)	(0.187)	(0.194)	(0.162)
N	204	204	204	204	204	204	204
Mean	0.11						
R-squared	0.49	0.65	0.68	0.67	0.74	0.78	0.86
Radio Emis.(t-1, t-2)	Y	Y	Y	Y	Y	Y	Y
Soc.Mob.Rep.(t-1, t-2)				Y	Y	Y	Y
Soc.Mob.Prev.(t-1, t-2)				Y	Y	Y	Y
Red Cross activity		Y	Y		Y	Y	Y
Pop/Dens/Dist Epic × Trend			Y			Y	Y

Robust Standard Errors in parentheses clustered by Prefecture × Semester
Controlling for Pref. FE, Time FE.
Red Cross activity: surveillance, transport, cholera kits
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: International Federation of the Red Cross in Guinea, April-December, 2015

The outcome variable is *refused burials* in 100'000 per capita, with mean (std. dev.) 0.11 (0.39). *Red Cross Radio* are the number of radio emissions aired and here we standardized the original variable which had mean (std. dev.) 0.85 (3.29). *Social Mobilis. Preventive* and *Social Mobilis. Response* are a standardized variable measuring the number of volunteers conducting door-to-door campaigns either for prevention or as a response to resistance behavior. The original variables had mean (std. dev.) 548 (1786) and 2793 (6729), respectively.

Table E.26: Refused Burials $t + 1$
Non standardized coefficients

Outcome: Refused burials in 100'000 per capita

	(1) t	(2) t+1	(3) t+2	(4) t+3
Red Cross Radio	0.029*	-0.053*	-0.034	-0.215
	(0.016)	(0.027)	(0.055)	(0.130)
Red Cross Radio × Social Mobilis. Preventive	-0.009	-0.002	0.004	0.030**
	(0.007)	(0.006)	(0.006)	(0.014)
Social Mobilis. Preventive	0.034	0.016	-0.035	-0.041
	(0.041)	(0.034)	(0.029)	(0.030)
Social Mobilis. Response	-0.013	-0.040*	-0.051*	-0.053
	(0.022)	(0.024)	(0.030)	(0.043)
N	238	204	170	136
Mean	0.12	0.11	0.10	0.10
R-squared	0.73	0.86	0.92	0.96
Radio Emis.(t-1, t-2)	Y	Y	Y	Y
Soc.Mob.Rep.(t-1, t-2)	Y	Y	Y	Y
Soc.Mob.Prev.(t-1, t-2)	Y	Y	Y	Y
Red Cross activity	Y	Y	Y	Y
Pop/Dens/Dist Epic × Trend	Y	Y	Y	Y

Robust Standard Errors in parentheses clustered by Prefecture × Semester
Controlling for Pref. FE, Time FE.
Red Cross activity: surveillance, transport, cholera kits
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data source: International Federation of the Red Cross in Guinea, April-December, 2015

The outcome variable is *refused burials* in 100'000 per capita, with mean (std. dev.) 0.11 (0.39). *Red Cross Radio* are the number of radio emissions aired and with mean (std. dev.) 0.85 (3.29). *Social Mobilis. Preventive* and *Social Mobilis. Response* are the number of volunteers conducting door-to-door campaigns either for prevention or as a response to resistance behavior with mean (std. dev.) 548 (1786) and 2793 (6729), respectively.

Table E.27: Public Good provision by access to Radio

Maximum number of public goods in 100'000 per capita

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Number of ETUs in 100k per cap	0.091***	-0.128***	-0.117**	-0.090	0.037*	0.041	0.018
	(0.032)	(0.048)	(0.055)	(0.057)	(0.022)	(0.077)	(0.067)
Number of Labs in 100k per cap	0.067***	-0.007	0.042*	0.034	0.002	-0.016	-0.017
	(0.022)	(0.025)	(0.022)	(0.025)	(0.009)	(0.040)	(0.040)
Number of CCC in 100k per cap	0.003	-0.009**	-0.008	-0.010*	0.012***	0.013**	0.006
	(0.007)	(0.004)	(0.006)	(0.005)	(0.003)	(0.006)	(0.005)
Any Radio		0.483***	0.420***	0.379***	0.888***	0.578***	0.023
		(0.042)	(0.051)	(0.050)	(0.028)	(0.051)	(0.100)
Any Rural Radio							0.625***
							(0.111)
N	331	331	331	331	331	331	331
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (ETU,Lab,CCC)	0.00	0.01	0.01	0.03	0.00	0.15	0.71
p-val (sum ETU,Lab,CCC)	0.00	0.01	0.19	0.32	0.03	0.64	0.93

(Robust SE). With region fixed effects (8 regions).

Excl. capital. Controls: population, population density, geographic area, distance to epicenter and their square.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: *Number of ETUs in 100k per capita*, *Number of Labs in 100k per capita* and *Number of CCCs in 100k per capita*, are maximum number of Ebola Treatment Unit (ETU), laboratories (Lab) and community care centers (CCC) in 100'000 per capita ever available, with mean (std. dev.) 0.04 (0.28), 0.07 (0.50) and 0.9 (2.4), respectively. ETUs and laboratories are created ad-hoc during the Ebola outbreak. CCCs are hospitals that exist prior to the epidemic outbreak. We control for variables correlated with the spread of the disease. The positive coefficient on *Number of ETUs in 100k per capita* in column (5) disappears when controlling for the total cumulative number of Ebola cases, Table E.28.

Table E.28: Public Good provision by access to Radio

Maximum number of public goods in 100'000 per capita
Controlling for the total cumulative number of Ebola cases at the end of the epidemic

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Number of ETUs in 100k per cap	0.054	-0.119**	-0.110*	-0.090	0.018	0.056	0.044
	(0.046)	(0.052)	(0.061)	(0.063)	(0.024)	(0.080)	(0.069)
Number of Labs in 100k per cap	0.054**	-0.004	0.044*	0.034	-0.004	-0.011	-0.008
	(0.023)	(0.025)	(0.023)	(0.027)	(0.011)	(0.041)	(0.041)
Number of CCC in 100k per cap	0.001	-0.009**	-0.008	-0.010*	0.011***	0.014**	0.007
	(0.007)	(0.004)	(0.006)	(0.005)	(0.003)	(0.006)	(0.005)
Any Radio		0.486***	0.422***	0.379***	0.883***	0.582***	0.018
		(0.043)	(0.051)	(0.050)	(0.029)	(0.051)	(0.100)
Any Rural Radio							0.639***
							(0.112)
N	331	331	331	331	331	331	331
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (ETU,Lab,CCC)	0.10	0.03	0.01	0.03	0.00	0.12	0.61
p-val (sum ETU,Lab,CCC)	0.04	0.03	0.31	0.39	0.34	0.52	0.60

(Robust SE). With region fixed effects (8 regions).
Excl. capital. Controls: population, population density, geographic area, distance to epicenter and their square, total cumulative number of Ebola cases.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: *Number of ETUs in 100k per capita*, *Number of Labs in 100k per capita* and *Number of CCCs in 100k per capita*, are maximum number of Ebola Treatment Unit (ETU), laboratories (Lab) and community care centers (CCC) in 100'000 per capita ever available, with mean (std. dev.) 0.04 (0.28), 0.07 (0.50) and 0.9 (2.4), respectively. ETUs and laboratories are created ad-hoc during the Ebola outbreak. CCCs are hospitals that exist prior to the epidemic outbreak. We control for variables correlated with the spread of the disease.

Table E.29: Summary statistics - Languages / Ethnic groups / Group belonging

	Not weighted	Population-weighted
Fractionalization	0.240	0.234
	(0.240)	(0.249)
Polarization	0.410	0.382
	(0.384)	(0.379)
Own group treated unfairly	1.635	1.315
	(1.040)	(1.008)
Ethnic belonging	0.880	0.763
	(0.645)	(0.560)
Peul	0.358	0.233
	(0.407)	(0.344)
Susu	0.146	0.161
	(0.291)	(0.298)
Forest	0.0769	0.0918
	(0.220)	(0.238)
Mande-Tan	0.0111	0.0133
	(0.0459)	(0.0515)
Malinke	0.303	0.421
	(0.353)	(0.421)
Mel	0.0961	0.0718
	(0.251)	(0.218)
Trust Most	0.275	0.288
	(0.181)	(0.153)
Trust President	1.832	2.091
	(0.855)	(0.835)
Trust Local Council	1.922	1.976
	(0.578)	(0.571)
Observations	115	115

By Sub-prefecture - Afrobarometer Round 5, 2013. Excluding capital.

Notes: *Fractionalization* and *Polarization* are constructed based on reported ethnic group.
Fractionalization measures the probability that two individuals belong to different groups. It's a Herfindahl index that goes from 0 (all belong to the same group), to 1 (total diversity). It is defined as $F = \sum_{i=1}^{m} n_i(1 - n_i)$, where m is the number of groups and n_i is the relative size of each group.
Polarization is defined as $P = \sum_{i=1}^{m} n_i^2(1 - n_i)$. In this case the group size matters beyond head count. It reaches its maximum when 2 equally sized groups face each other. The correlation between both measures is 0 at intermediate levels, negative at low levels of F, and positive at high levels of F.
Own group treated unfairly is a categorical variable with values 0 (never treated unfairly), 1 (don't know), 2 (sometimes treated unfairly), 3 (often treated unfairly), 4 (always treated unfairly).
Ethnic belonging is a categorical variable with values higher numbers indicating stronger ethnic belonging rather than a national identity. It takes values 0 (feel only national identity), 1 (feel more national identity), 2 (feel equally national as ethnic identity), 3 (feel more ethnic identity), 4 (feel only ethnic identity).
Peul, Susu, Forest, Malinke, Mande, Mel are constructed by the author aggregating ethnic groups by language group.
Trust Most is 1 if most people can be trusted and 0 if one must be very careful. *Trust President* and *Trust Local Council* takes values 0 (no trust) 1 (little trust), 2 (some trust) and 3 (a lot).

Table E.30: Ethnic groups / Languages by access to Radio

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Peul	-0.153	0.226	-0.154	-0.192	-0.024	-0.099	-0.083
	(0.226)	(0.173)	(0.179)	(0.172)	(0.132)	(0.233)	(0.209)
Susu	-0.027	-0.216	0.130	0.077	-0.052	-0.576**	-0.540**
	(0.216)	(0.189)	(0.183)	(0.185)	(0.133)	(0.255)	(0.247)
Forest	-0.025	0.415***	0.337**	0.200	-0.219**	0.284	0.438**
	(0.283)	(0.145)	(0.142)	(0.160)	(0.098)	(0.190)	(0.188)
Mande-Tan	0.066	1.885***	1.749***	1.876***	-0.094	-0.153	-0.087
	(0.631)	(0.387)	(0.520)	(0.468)	(0.403)	(0.853)	(0.694)
Malinke	0.047	-0.108	0.018	-0.129	-0.103	0.277	0.349
	(0.216)	(0.124)	(0.137)	(0.150)	(0.105)	(0.236)	(0.225)
Mel	-0.288	0.047	0.097	0.033	-0.184*	0.341*	0.470***
	(0.272)	(0.125)	(0.130)	(0.130)	(0.094)	(0.178)	(0.175)
Any Radio		0.386***	0.401***	0.354***	0.905***	0.694***	0.060
		(0.070)	(0.071)	(0.070)	(0.044)	(0.079)	(0.235)
Any Rural Radio							0.701***
							(0.250)
N	112	112	112	112	112	112	112
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (all lang.)	0.78	0.00	0.00	0.00	0.15	0.02	0.01
p-val (sum lang.)	0.76	0.01	0.01	0.02	0.33	0.95	0.61

(Robust SE)

Excl. capital. Controls: population, geographic area, distance to epicenter, region fixed effects (8 regions).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: *Peul, Susu, Forest, Malinke, Mande, Mel* are constructed by the author aggregating ethnic groups by language group.

Table E.31: Language Index by access to Radio

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Fractionalization	0.408	0.439	0.345	0.326	-0.224	0.841**	0.845**
	(0.413)	(0.351)	(0.405)	(0.374)	(0.197)	(0.331)	(0.366)
Polarization	-0.050	-0.348	-0.101	-0.123	0.151	-0.344	-0.194
	(0.258)	(0.210)	(0.237)	(0.216)	(0.116)	(0.213)	(0.234)
Language-Index	0.007	0.004	-0.003	-0.003	-0.002	-0.012***	-0.013***
	(0.007)	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)	(0.005)
Any Radio		0.541***	0.590***	0.528***	0.909***	0.575***	-0.038
		(0.085)	(0.079)	(0.080)	(0.039)	(0.083)	(0.205)
Any Rural Radio							0.717***
							(0.220)
N	112	112	112	112	112	112	112
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (all lang.)	0.19	0.13	0.30	0.49	0.56	0.00	0.00
p-val (sum lang.)	0.08	0.57	0.21	0.27	0.45	0.00	0.00

(Robust SE)

Excl. capital. Controls: population, geographic area, distance to epicenter, region fixed effects (8 regions).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: *Fractionalization* and *Polarization* are constructed based on reported ethnic group. *Language-Index* is an index based on reported language.

Fractionalization measures the probability that two individuals belong to different groups. It's a Herfindahl index that goes from 0 (all belong to the same group), to 1 (total diversity). It is defined as $F = \sum_{i=1}^{m} n_i(1 - n_i)$, where m is the number of groups and n_i is the relative size of each group.

Polarization is defined as $P = \sum_{i=1}^{m} n_i^2(1-n_i)$. In this case the group size matters beyond head count. It reaches its maximum when 2 equally sized groups face each other. The correlation between both measures is 0 at intermediate levels, negative at low levels of F, and positive at high levels of F.

Table E.32: Trust in people by access to Radio

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Trust Neighbours	0.111	-0.129	-0.144*	-0.048	0.114*	0.153	0.091
	(0.151)	(0.093)	(0.078)	(0.092)	(0.061)	(0.133)	(0.137)
Trust Most	-0.048	0.021	0.017	-0.036	-0.040	-0.352	-0.330
	(0.188)	(0.150)	(0.143)	(0.145)	(0.086)	(0.230)	(0.226)
Trust Family	-0.003	-0.273**	0.188	0.224*	0.134	0.354*	0.281
	(0.206)	(0.133)	(0.136)	(0.132)	(0.101)	(0.189)	(0.172)
Trust Others	-0.086	0.007	-0.103	-0.105	-0.001	-0.028	-0.028
	(0.090)	(0.063)	(0.067)	(0.065)	(0.042)	(0.083)	(0.080)
Any Radio		0.381***	0.419***	0.362***	0.908***	0.665***	0.171
		(0.075)	(0.078)	(0.077)	(0.042)	(0.078)	(0.205)
Any Rural Radio							0.545**
							(0.228)
N	112	112	112	112	112	112	112
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (all trust)	0.90	0.08	0.01	0.20	0.19	0.25	0.43
p-val (sum trust)	0.92	0.02	0.78	0.83	0.07	0.52	0.94

(Robust SE)

Excl. capital. Controls: population, geographic area, distance to epicenter, region fixed effects (8 regions).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.33: Trust in Institutions by access to Radio

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Trust Leader	0.097	-0.102	-0.120*	-0.146**	-0.023	-0.198***	-0.184***
	(0.082)	(0.067)	(0.072)	(0.071)	(0.041)	(0.071)	(0.068)
President	0.105	0.014	0.057	0.093	0.005	0.041	0.038
	(0.077)	(0.088)	(0.078)	(0.089)	(0.059)	(0.122)	(0.122)
Local Council	-0.068	-0.045	-0.057	-0.082	-0.008	0.129*	0.134*
	(0.066)	(0.059)	(0.051)	(0.051)	(0.035)	(0.075)	(0.072)
Parliament	0.014	0.012	0.050	-0.006	-0.061	-0.002	0.036
	(0.083)	(0.064)	(0.058)	(0.067)	(0.050)	(0.090)	(0.084)
Electoral C.	-0.085	-0.112	-0.090	-0.052	0.074	-0.099	-0.144
	(0.097)	(0.075)	(0.081)	(0.091)	(0.054)	(0.116)	(0.118)
Tax Auth.	0.082	-0.083	0.023	0.031	0.018	-0.000	-0.012
	(0.087)	(0.052)	(0.059)	(0.060)	(0.036)	(0.075)	(0.075)
Any Radio		0.405***	0.422***	0.365***	0.910***	0.704***	0.137
		(0.075)	(0.076)	(0.080)	(0.045)	(0.089)	(0.218)
Any Rural Radio							0.623***
							(0.229)
N	112	112	112	112	112	112	112
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (all trust)	0.55	0.02	0.22	0.27	0.72	0.06	0.05
p-val (sum trust)	0.29	0.00	0.17	0.14	0.91	0.24	0.21

(Robust SE)

Excl. capital. Controls: population, geographic area, distance to epicenter, region fixed effects (8 regions).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.34: Trust in Institutions by access to Radio - controlling for urban infrastructure

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Fractionalization	0.692	-0.192	-0.730*	-0.594	0.042	0.553	0.521
	(0.511)	(0.360)	(0.369)	(0.362)	(0.169)	(0.407)	(0.377)
Polarization	-0.306	0.104	0.357	0.171	-0.077	0.014	0.071
	(0.302)	(0.223)	(0.229)	(0.230)	(0.108)	(0.257)	(0.240)
Peul	-0.258	0.292	-0.108	-0.282	-0.223	-0.051	0.116
	(0.319)	(0.206)	(0.148)	(0.171)	(0.177)	(0.300)	(0.278)
Susu	-0.005	-0.123	0.102	-0.151	-0.355**	-0.510	-0.244
	(0.333)	(0.237)	(0.192)	(0.217)	(0.173)	(0.344)	(0.346)
Forest	-0.189	0.563**	0.548***	0.180	-0.481***	0.183	0.545
	(0.350)	(0.241)	(0.195)	(0.250)	(0.171)	(0.328)	(0.349)
Mande-Tan	0.142	1.797***	2.041***	2.051***	0.092	-0.183	-0.252
	(0.793)	(0.593)	(0.394)	(0.454)	(0.221)	(0.628)	(0.573)
Malinke	-0.018	-0.113	-0.034	-0.207	-0.140	0.028	0.133
	(0.232)	(0.155)	(0.143)	(0.148)	(0.111)	(0.228)	(0.216)
Mel	-0.325	0.159	0.263*	0.026	-0.415***	0.093	0.405
	(0.309)	(0.181)	(0.153)	(0.189)	(0.124)	(0.259)	(0.291)
Trust Leader	0.113	-0.021	-0.020	-0.075	-0.093**	-0.163*	-0.093
	(0.082)	(0.069)	(0.066)	(0.067)	(0.045)	(0.086)	(0.082)
President	0.078	0.065	0.163*	0.164*	-0.060	-0.038	0.007
	(0.105)	(0.084)	(0.091)	(0.093)	(0.073)	(0.130)	(0.109)
Local Council	0.020	0.046	0.008	-0.050	-0.085	0.121*	0.184**
	(0.091)	(0.071)	(0.061)	(0.068)	(0.054)	(0.070)	(0.075)
Parliament	-0.042	0.047	0.114*	0.072	-0.047	-0.025	0.011
	(0.080)	(0.067)	(0.061)	(0.079)	(0.051)	(0.086)	(0.077)
Electoral C.	-0.044	-0.070	-0.167*	-0.112	0.114	0.111	0.025
	(0.128)	(0.084)	(0.100)	(0.101)	(0.072)	(0.116)	(0.098)
Tax Auth.	0.034	-0.071	0.009	0.041	0.060	0.001	-0.044
	(0.089)	(0.063)	(0.052)	(0.053)	(0.039)	(0.073)	(0.072)
Any Radio		0.384***	0.379***	0.315***	0.901***	0.649***	-0.028
		(0.085)	(0.079)	(0.079)	(0.050)	(0.098)	(0.214)
Any Rural Radio							0.751***
							(0.228)
N	112	112	112	112	112	112	112
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (all lang.)	0.72	0.01	0.00	0.00	0.00	0.57	0.37
p-val (sum lang.)	0.71	0.02	0.00	0.11	0.06	0.78	0.65
p-val (all trust)	0.72	0.76	0.05	0.22	0.26	0.07	0.05
p-val (sum trust)	0.27	0.98	0.31	0.74	0.12	0.96	0.53

(Robust SE)

Excl. capital. Controls: population, geographic area, distance to epicenter, region fixed effects (8 regions).

Additional controls: urban, electricity, piped water, health centers, markets, police.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: *Fractionalization* and *Polarization* are constructed based on reported ethnic group. On the other hand *Peul, Susu, Forest, Malinke, Mande, Mel* are constructed by the author aggregating ethnic groups by language group. See Table E.29 for definitions.

Table E.35: Trust in Institutions by access to Radio - controlling for urban infrastructure
With next period Trust in Local Council

	(1) Any Radio	(2) National	(3) Private	(4) Private-Urt.	(5) Any Rural Radio	(6) Own Rural	(7) Own Rural
Fractionalization	0.747	-0.286	-0.707*	-0.541	0.032	0.510	0.489
	(0.505)	(0.362)	(0.369)	(0.369)	(0.171)	(0.417)	(0.398)
Polarization	-0.294	0.157	0.400*	0.197	-0.039	0.013	0.039
	(0.314)	(0.226)	(0.234)	(0.242)	(0.110)	(0.270)	(0.262)
Peul	-0.300	0.394**	-0.147	-0.276*	-0.125	-0.080	0.003
	(0.277)	(0.176)	(0.133)	(0.142)	(0.149)	(0.280)	(0.238)
Susu	-0.030	-0.020	0.145	-0.088	-0.213	-0.586	-0.445
	(0.311)	(0.217)	(0.206)	(0.240)	(0.150)	(0.362)	(0.363)
Forest	-0.188	0.388*	0.549***	0.265	-0.401***	-0.022	0.244
	(0.315)	(0.209)	(0.192)	(0.220)	(0.147)	(0.306)	(0.303)
Mande-Tan	0.062	1.741***	2.033***	2.057***	0.152	-0.304	-0.405
	(0.776)	(0.581)	(0.396)	(0.425)	(0.241)	(0.642)	(0.600)
Malinke	-0.062	-0.148	-0.051	-0.219	-0.127	-0.021	0.063
	(0.218)	(0.153)	(0.145)	(0.153)	(0.104)	(0.227)	(0.208)
Mel	-0.312	0.153	0.264*	0.063	-0.366***	0.043	0.286
	(0.295)	(0.171)	(0.151)	(0.175)	(0.101)	(0.231)	(0.241)
Trust Leader	0.104	-0.046	-0.033	-0.074	-0.088**	-0.186**	-0.128
	(0.082)	(0.065)	(0.067)	(0.063)	(0.043)	(0.089)	(0.086)
President	0.062	0.075	0.168*	0.164*	-0.045	-0.051	-0.021
	(0.108)	(0.073)	(0.090)	(0.091)	(0.074)	(0.132)	(0.114)
Local Council (2015)	-0.069	-0.011	-0.013	-0.037	0.001	-0.029	-0.029
	(0.055)	(0.043)	(0.047)	(0.051)	(0.026)	(0.061)	(0.061)
Parliament	-0.034	0.022	0.106	0.067	-0.067	-0.020	0.024
	(0.080)	(0.066)	(0.067)	(0.085)	(0.054)	(0.094)	(0.091)
Electoral C.	0.000	-0.074	-0.160*	-0.101	0.089	0.144	0.084
	(0.131)	(0.070)	(0.093)	(0.090)	(0.073)	(0.121)	(0.104)
Tax Auth.	0.026	-0.084*	-0.007	0.017	0.028	0.022	0.003
	(0.082)	(0.050)	(0.052)	(0.054)	(0.039)	(0.065)	(0.059)
Any Radio		0.385***	0.371***	0.302***	0.895***	0.651***	0.056
		(0.084)	(0.076)	(0.077)	(0.051)	(0.094)	(0.228)
Any Rural Radio							0.665***
							(0.244)
N	110	110	110	110	110	110	110
Mean	0.587	0.283	0.216	0.193	0.459	0.282	0.282
p-val (all lang.)	0.78	0.01	0.00	0.00	0.00	0.49	0.27
p-val (sum lang.)	0.59	0.02	0.00	0.04	0.10	0.50	0.85
p-val (all trust)	0.58	0.42	0.05	0.21	0.38	0.36	0.41
p-val (sum trust)	0.56	0.26	0.56	0.76	0.21	0.45	0.67

(Robust SE)
Excl. capital. Controls: population, geographic area, distance to epicenter, region fixed effects (8 regions).
Additional controls: urban, electricity, piped water, health centers, markets, police.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: *Fractionalization* and *Polarization* are constructed based on reported ethnic group. On the other hand *Peul, Susu, Forest, Malinke, Mande, Mel* are constructed by the author aggregating ethnic groups by language group. See Table E.29 for definitions.